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Are technologies contagious among countries?

A worldwide analysis of infrastructural technology adoption

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Abstract

Introduction Anthropogenic climate change and increasing tensions between countries pose a serious threat to international security. On the one hand, governments around the world turn towards technological solutions as a remedy to environmental problems. Thus, securing access to clean infrastructural technologies is crucial at a global level. On the other hand, the recent trade war between the USA and China signals the unfolding of a New Cold War. Despite the similarities to the frictions between the Soviet Union and the USA in the postwar period, this New Cold War is much less about ideology and more about technology. Yet, little is known about the influence of international relations on cross-country technology diffusion.

Theory This research takes an interdisciplinary approach, it combines Roger's paradigm of diffusion of innovations, social contagion theory and the realist approach to international relations to build a conceptual framework. The hypotheses are tested quantitatively to examine how alliances affect technology adoption decisions by national governments.

Methodology Logistic regression is used to analyze the secondary data on the worldwide adoption of eight infrastructural technologies (from the energy, transportation, and space sectors) between 1954 and 2012 on a sample of 161 countries.

Results The results showed that membership in alliances had positive impact on the adoption likelihood. However, the influence of the alliance leader by the leader differed for the technological sectors. The finding that the similarity of political systems was disproved, highlights the role of interaction between countries in the diffusion process.

Conclusion and Discussion The results suggest that the theory of social contagion can be applied to the field of international relations to explain technology adoption among countries. The findings imply that countries can use the tools of foreign policy to promote their technologies but also to obtain access to the crucial technologies. This research contributed to the theoretical understanding of the drivers of adoption and proved the worthiness of interdisciplinary research designs. Lastly, "contagiousness" of specific technologies seems to play a role in the dynamics of diffusion.

Keywords: international relations, social contagion, technology diffusion, technology adoption, infrastructural technologies

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List of Abbreviations

Abbreviation	Description
CINC	Composite Indicator of National Capability
COW	The Correlates of War Project
CSP	Concentrating solar-thermal power
EIA	Energy Information Administration
FAO	Food and Agriculture Organization
GDP	Gross domestic product
GAM	Generalized additive model
GLM	Generalized linear model
HRSR	Higher-speed rail
HSR	High-speed rail
IAEA	International Atomic Energy Agency
IEA	International Energy Agency
IR	International relations
IRENA	International Renewable Energy Agency
IT	Information technology
MW	Mega Watt
NATO	North Atlantic Treaty Organisation
NASA	National Aeronautics and Space Administration
OECD	Organisation for Economic Co-operation and Development
PV	Solar photovoltaic
ROC	Receiver operating characteristic
TGV	Train à grande vitesse
UNESCO	The United Nations Educational, Scientific and Cultural Organization
UNOOSA	United Nations Office for Outer Space Affairs
UIC	Union Internationale des Chemins de Fer
UIS	UNESCO Institute for Statistics
UK	United Kingdom
USA	United States of America
USPAT	United States Patent and Trademark Office
USSR	Union of Soviet Socialist Republics
VIF	Variance inflection factor
WWII	World War II

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1. Introduction

The successful launch of the Earth's first satellite Sputnik in 1957 intensified the technological race and the tensions of the Cold War. The international frictions between the countries allied with the Soviet Union (USSR) and the United States of America (USA) had a substantial impact on technology as they pushed the policymakers to accelerate technological development.

After the fall of the Berlin Wall and at the verge of the democratization wave, American political scientist Francis Fukuyama declared the "end of history": the victory of liberal democracy and capitalism (Fukuyama, 1992). On this wave of optimism, the concerns about international security eroded and another cold war became unthinkable to many people (Ferguson, 2019). Postwar globalization paced up and brought about social, economic, political, and technological change. It contributed to the technological breakthroughs and to the rapid diffusion of technologies (Comin & Hobijn, 2010; Tellis & Chandy, 2006).

However, the international tensions intensified with the resurgence of Russia, and ever more so, with the rapid development of China during the last three decades. In particular, the autocratic ruling in Russia and the economic rise of communist China coupled with its diplomatic efforts in Africa became the sources of rising concerns in the Western world (Jakobson, 2009; Werrell & Femia, 2020). The trade war between the USA and China is an excellent manifestation of these new developments, oftentimes referred to as the unfolding of a New Cold War (Yao, 2021). Despite superficial similarity to the postwar conflict, this New Cold War is different. First, it is much less about ideology but much more about technology and access to markets. For instance, driven by the Chinese threat to the supremacy of American technology, the USA pressured the German government to refrain the country from closing a deal to upgrade the German networks with the Chinese 5G technology (Jaisal, 2020). Second, the relative difference in power between China and the USA is much smaller than it was in the case of the Soviet Union. Third, the economies of the "sides of the war" are deeply connected (Yao, 2021). Furthermore, the sanctions imposed on Russia's critical resources and technologies pushed the foreign policy of the country towards China and intensified technological exchange between these two countries (Gould-Davies, 2020). These examples show that international relations can influence technological development and affect the patterns of cross-country technology diffusion.

On the other hand, the end of the Cold War coincided with the rise of the threat to international security posed by anthropogenic climate change. Despite the increasing awareness of the imminent climate crisis, oftentimes the national mitigation policies failed (Latin, 2012). Instead, the governments put hope in the technology as a solution to the pressing environmental problems which is shown by the rising political interest in clean technologies (Rao & Kishore, 2010; Safarzyńska et al., 2012; Vasseur & Kemp, 2015). Environmentally sound technologies offer unprecedented opportunities to progress towards sustainability and are essential for achieving sustainable development goals (Fadly & Fontes, 2019; Rao & Kishore, 2010). Even though the consequences of climate change will be less dramatic to some countries than others, this burning issue remains a global concern. For that reason, all countries need to be able to use clean technologies to ensure the stability of the international system. Thus, the diffusion of clean technologies has a crucial role in the globalized world.

Diffusion of technologies starts in the innovative regions (Easterly et al., 1994). Lead firms in innovative countries try to export their technology and know-how (Cohen, E., 2006). Subsequently, other regions "catch up" by adopting the new technology developed in the innovation center (Grübler, 1998a). The diffusion process is gradual and cumulative. Typically, it starts with a slow implementation phase by early adopters. Next, it is followed by rapid diffusion due to the high adoption rate. Finally, the diffusion slows down when most of the potential users have adopted the technology (Grübler, 1998). Plotting of the diffusion process over time results in so-called S-curves (Diebolt et al., 2016; Geroski, 2000).

Historically, a vast majority of countries has chosen to adopt technologies from abroad instead of developing them on their own (Huang & Shih, 2012). They were thus concerned with upgrading to more advanced technologies. The adoption of technologies is less costly than developing new ones and can serve as a way to boost technological growth, especially in the case of developing countries (Lee, 2001). Foreign policy comes to play when countries acquire technology from abroad because they have to secure access to it from the other countries. In addition, national governments can shape the technological landscapes through domestic policy intervention (Lee, 2001; Nallari, 2011; Warwick, 2013). The level of engagement can range from a laissez-faire approach, through the support of factor conditions for innovation, to active selection and targeting of specific technologies (Atkinson & Ezell, 2012). Some policies can aim at prioritization of capital-intensive heavy industries such as infrastructure projects (Wang, L. & Wen, 2018). Infrastructural projects create positive externalities and enable network effects that benefit societies (Hall & Khan, 2003). Such projects can be realized either by the national government or in cooperation of the public and private sector (Atkinson & Ezell, 2012).

The infrastructural technologies from the sectors of energy, transportation and space are particularly relevant to tackling the challenges stemming from climate change and to contributing to sustainable development. The electricity generation sector is a vital building block of modern societies. The traditional energy sources based on fossil fuels are the sources of environmental problems such as emissions of greenhouse gases, air pollution, etc. Thus, the energy sector is one of the key sectors where the action is needed to achieve sustainable development (Dincer & Rosen, 1999; Dincer, 2000). Similarly, the transportation sector is responsible for negative environmental impacts. The strategies towards sustainability include rethinking of car ownership and use, development of more efficient vehicles, investments in public transport including railways (Clark Shedd et al., 2020; Jehanno et al., 2011), less polluting shipping and use of telecommunications to annihilate the need to travel (Satoh &

Lan, 2007). Lastly, space technologies can be likewise leveraged to contribute to sustainable development. They can support a range of activities such as weather forecasting, agricultural planning, disaster management, enable distance education, among others (Di Pippo, 2019).

Yet, little is known about the determinants of the adoption of infrastructural technologies, in the context of international relations. The S-curves are descriptive and have little explanatory power (Grübler, 1998b). Hence, it is valuable to understand technology adoption patterns for countries, and what factors affect the rates of diffusion. In this regard, diffusion is a dynamic consequence of adoption and makes technology adoption a particularly interesting topic for research.

Technology adoption and the adoption determinants have been studied in many disciplines. The diversity is present in regard to unit of analysis, scope, aim and approach. For brevity, the results of the literature survey are synthesized to give an overall insight into the current streams of research. While many studies examined adoption by the consumers, only a few studies took countries as an analytical unit and typically in conjunction with the case study approach (Aggarwal et al., 2018; Albors et al., 2006; Vasseur & Kemp, 2015). Several studies included technology as the dependent variable, which seems the most dominant unit of analysis. Scholars have studied a wide range of technologies: from basic agricultural and manufacturing technologies such as fertilizers and textiles (Aggarwal et al., 2018; Baldwin & Raffiquzzaman, 1998; Comin & Hobijn, 2004), through infrastructural technologies including electricity generation and transportation (Comin & Hobijn, 2004; Comin & Hobijn, 2010), to the high-tech technologies such as microelectronics, computers, communication and IT and renewable energy (Albors et al., 2006; Caselli & Coleman, 2001; Comin et al., 2012; Vasseur & Kemp, 2015). These studies offered insights into technology-specific factors in the diffusion process. An interesting research subcategory is study of adoption time lags (Baldwin & Raffiquzzaman, 1998) and spatial aspects (Diebolt et al., 2016). Furthermore, researchers have analyzed the process using various levels of analysis: micro- (Albors et al., 2006; Baldwin & Raffiquzzaman, 1998), meso- (Vasseur & Kemp, 2015), and macro-; with the most extensive work carried out by Diego Comin and his colleagues. Another way to classify the current research is the way the adoption was measured. Two distinct approaches were identified: extensive and intensive margin. In the extensive margin research, adoption is treated as a binary decision, with the measure of adoption as the share of potential users that have adopted a technology (Comin et al., 2006) . In the intensive margin approach, the measure is built on the frequency and intensity of use (Diebolt et al., 2016). The adoption determinants have attracted the attention of researchers from different disciplines. Nonetheless, the research has been mostly focused on the economic factors, especially when technology is perceived as a driver of growth (Aggarwal et al., 2018; Caselli & Coleman, 2001; Comin & Hobijn, 2010; Gopalakrishnan & Damanpour, 1997). The studies from the non-economic stream consider sociological and human factors (Caselli & Coleman, 2001; Comin & Mestieri, 2014; Gopalakrishnan & Damanpour, 1997). There is little research on political determinants of adoption, with the exception of a case study of the impact of the political regime on the adoption of television and the internet (Corrales & Westhoff, 2006). In particular, political aspects are important regarding large infrastructural technologies in the energy, transportation and communication sectors. Well-functioning infrastructures are vital because national economic development depends on them (Akitoby et al., 2007; Freeman, 2004). National governments are generally closely involved in the choice of infrastructure technology, as the choice of technology has implications for other domains such as spatial planning, national security, industrial policy and, more recently, sustainability.

In brief, despite the abundance of research on the determinants of technology adoption, to date, there was no study taking the perspective of international relations in studying the diffusion of the infrastructural technologies. Thus, a political point of view on technology adoption by national governments allows considering the role of international relations in technology diffusion. As national governments are generally financing the infrastructure, the political ties between countries are likely to affect technology diffusion. Analogous to friends affecting the adoption of a new product, one can expect that allied countries affect their choice of infrastructural technology. Moreover, there is a lack of studies taking a worldwide approach. Comin and Mestieri (2014) have pointed out the need for further cross-country research of technology adoption determinants. Furthermore, Diebolt et al. (2016) call for a more interdisciplinary approach to better explicate the complexity of the process. Currently, there are meta-studies with a large sample of technologies but only a few with large samples of countries. It is not fully understood why certain countries adopt new technologies at different rates and what global political mechanisms influence the diffusion rate across the potential adopters. Thus, the main question of this study is:

"How do international relations between countries affect infrastructural technology adoption decisions by national governments?"

This research aims to advance the theoretical understating of the infrastructural technology diffusion by quantitatively identifying the determinants that affected technology adoption by countries worldwide, and over time. The political angle of the study can facilitate shedding light on what factors of the political landscape are the most prevalent ones. Using the country as a unit of analysis allows generating knowledge relevant for the governments and policymakers. Thus, such an approach enables investigating how international relations influenced technology diffusion and adoption in the past and use these empirical grounds to formulate policy advice for the governments. Furthermore, the study aims to contribute to the innovation sciences. The study is newsworthy because it applies a novel approach of linking the country's adoption decision to its international relations and its characteristics. Lastly, taking a global approach opens up the opportunity to provide the big picture and distill what adopting countries have in common to produce generalizable conclusions. Lastly, the focus on energy, transportation, and space technologies is motivated by global sustainability challenges.

Each of the selected sectors can contribute to sustainability transitions. Including multiple technologies in the study provides richer context and allows achieving deeper understanding compared to a study of a single technology. Thus, a better understanding of the diffusion of these technologies can be of benefit to society.

This research will analyze eight technologies that: (i) are high-tech and have infrastructural character, (ii) have been widely disseminated after World War II (WWII), (iii) contribute to sustainable development. The technologies selected for the are nuclear, solar, wind and marine power; higher- and high-speed rail, and telecommunication and meteoroidal satellites.

These criteria for the scope have been selected for several reasons. First, the high-tech and infrastructural character of technologies suggest an involvement of the national government because adoption of large-scale technologies is often a decision of collective actors (Wejnert, 2002). Second, over the last decades, governments and institutions put the effort into collecting statistics and facts relevant for innovation and diffusion (Fagerberg et al., 2010). Thus, focusing on post-WWII developments and widely adapted technologies allows for quantitative research design. Lastly, this time scope is ideal for capturing the process from its beginning.

This thesis is organized as follows. Chapter 2 deals with the theoretical and conceptual framework and provides background information on the technologies selected for the study. The methodology is developed in chapter 3. Chapters 4 and 5 present and conclude on the results. Lastly, the discussion points are presented in chapter 6.

2. Theory

This chapter deals with the theoretical framework and conceptual framework. It introduces the foundations and the main building blocks of the theories as well as highlights differences and similarities between them. Then, it argues how the concepts can be related to derive hypotheses. Lastly, it provides background information and delineates the technologies chosen for the study.

The conceptual framework of this study was built upon the theories of diffusion of innovations, social contagion, and the realist school of thought in international relations (IR). They were selected to build the framework because all three theories overlap in the sense that they deal with agents embedded in networks. In the diffusion of innovations and social contagion, the agents are individuals embedded in social networks, but the theories offer different vantage points. In IR, the agents are states in the international system.

Before the theories are discussed in detail, it must be stressed that each was applied for a slightly different purpose. The diffusion of innovations theory is used primarily to introduce the concepts necessary for describing innovation, the social contagion lays the groundwork for understanding how the interconnectedness of the agents affects the diffusion; and finally, IR is employed to describe the international state system as well as the mechanisms of diffusion that occur within it.

2.1. Diffusion of innovations

The conceptual framework for describing the diffusion of innovations has been drawn upon the work of Rogers (2003). Roger’s model offers a versatile conceptual toolkit for the analysis of innovation and has been widely used in diffusion studies of technological innovation. Even though it was originally developed to explain the spread of new products among individuals, it can be applied to other social systems. Before discussing the transferability and applicability of the diffusion of innovations theory to this research, the main elements of the theory explained.

Diffusion is the process of proliferation of innovation in time within a social system from a source to an adopter, typically through channels of communication and influence. Communication and influence affect the likelihood of adopting of innovation by an actor. An actor is understood as a social entity; for example, individuals, groups, and organizations (Rogers, 2003). Thus, the four elements of the diffusion process are: (i) innovation, (ii) communication channels, (iii) time, (iv) social system.

Innovation is conceptualized as an idea, practice, or object viewed as new by a unit of adoption. The notion of newness from the user perspective is central in distinguishing between invention and innovation (Rogers, 2003). Invention is understood analogously to the classical linear model of innovation, it denotes the development of a new product or process and its practical application (Godin, 2006). In Roger’s model, a product or process is considered an innovation, even if there was a time gap between invention and the first use of a product if the product is novel to the user. Once a decision-making unit receives information about innovation, it forms an attitude towards it and decides either to adopt it or to reject it. *Adoption* is a deliberate decision to make use of an innovation (Rogers, 2003).

Rogers' theory (2003) points out that the words innovation and technology are often used interchangeably. Therefore, it is important to examine how they relate. *Technology* is defined as a design for instrumental action reducing uncertainty about the cause-effect relationship related to the desired outcome (Rogers, 2003). It is an inseparable combination of hardware tool embodying the technology in a physical object and software comprising the information about the tool. There is a close relationship between hardware and software, a technology is usually a mixture of both (Rogers, 2003, p. 28). Roger's definition of technology is somewhat "broad". However, this broadness allows to include different variants of the same technology under one umbrella term. Such conceptualization of technology is suitable for this study, given that it global, historical approach. Hence, in the context of this study, innovation is understood as a technology that has not been used before by a country.

Communication is the process of creation and exchange of information between social entities, happening through the *communication channels*. Diffusion is a special kind of communication and occurs when information about the innovation is exchanged. It a highly social process involving interpersonal communication relationships. At the level of individuals, communication occurs more frequently and is more effective between individuals that are similar in certain attributes. Homophily is the degree of similarity between the attributes of interacting individuals (Rogers, 2003).

Time is a vital component of the diffusion process because the adoption rate and adopter categorization include a time dimension. Agents are innovative when they decide to adopt relatively early compared to the members of their social system. They can be classified into five categories: innovators, early adopters, early majority, late majority, and laggards (Rogers, 2003). Innovators are the first ones to experiment with new ideas or products, early adopters typically hold a leadership role and act as role models for other agents, both early and late majority adopters deliberately take more time and base their decision upon evaluation of those who have already adopted the innovation, laggards are the most skeptical and decide to adopt only if the innovation has been successfully adopted by the others.

The relative speed of adoption by the members of the social system is called the *rate of adoption*. The cumulative number of adopters plotted over time results in a distribution in an S-shaped curve (Diebolt et al., 2016; Geroski, 2000). First, few agents adopt the innovation, with the increasing number of adopters the adoption rate increases, and the curve becomes steeper. Finally, the diffusion process ends when there are only a few agents who have not adopted the innovation, the S-curve reaches its asymptote (see Figure 2-1).

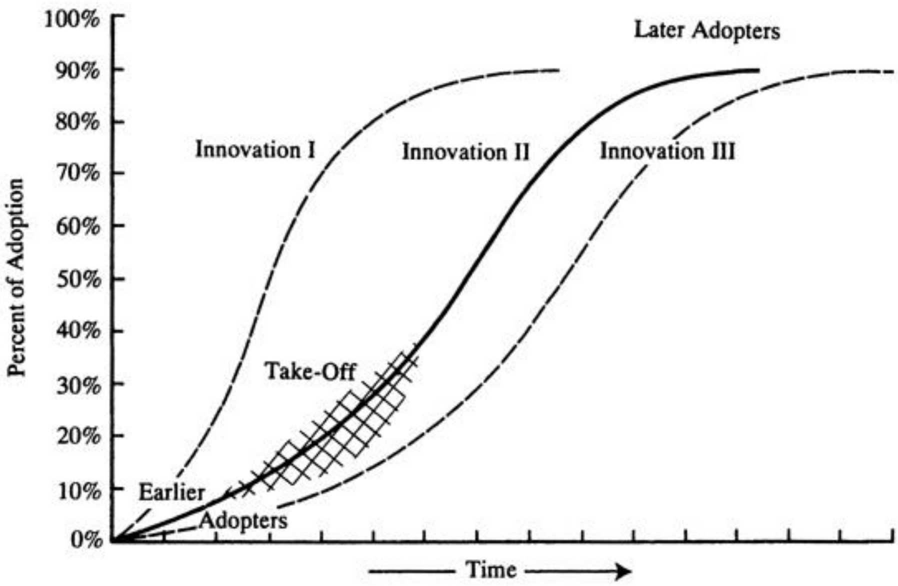

Figure 2-1 *The diffusion process. Reprinted from (Rogers, 2003).*

A Social system is a set of interconnected and distinguishable agents. The arrangements between agents constitute the structure of the social system. Because diffusion takes place in a social system, it is influenced by its structure. Two important aspects of the social system are norms and opinion leadership. Norms are the established patterns of behavior of the members of the social system, they guide the expected behavior of the agents. Opinion leadership is the ability of an agent to informally influence in the desired way the attitudes of other entities in the social system. Opinion leaders act as role models for the followers, regarding innovation behavior. Thus, opinion leaders have either positive or negative impact on the follower's attitude towards innovation. It is important to distinguish between opinion leaders and change agents. While opinion leaders influence the attitudes, change agents actively seek to influence adoption decisions. Change agents are typically different (heterophilous) from the entities they try to influence. Aides are change agents who homophilous with the target entities and are more effective at communication (Rogers, 2003).

In brief, Roger's model is built around the notion of innovation comprising the idea of newness from the perspective of an adopting unit. Diffusion is thus a temporal process of adoption of innovation by members of a social system who use communication channels to exchange information about it.

2.2. Social contagion

Observing diffusion from the vantage point of influences between adopters and non-adopters allows seeing diffusion as a temporal process of *social contagion*. Using this lens has two advantages. First, it enables zooming in on the process underlying the diffusion of technologies (Angst et al., 2010). Second, it extends the analysis from investigating only the characteristics of the adopting entity to investigating the relationships between them.

The conceptualization of contagion originated in biological sciences and has been used to elucidate the spread of disease through close contact between individuals (Angst et al., 2010; Langley et al., 2012). Consequently, the dynamics of the phenomenon are comparable to those of an epidemic (Young, 2009). The idea of contagion spread to other disciplines such as sociology, marketing, and organizational studies. It has been applied in these disciplines to explain the contagiousness of airplane hijacking (Holden, 1986), the spread of consumer products (Van den Bulte & Stremersch, 2004) or the role of social influence in the diffusion of civil services restructuring (Tolbert & Zucker, 1983). It has been also applied to explain the diffusion of innovation, with two influential studies of hybrid seed corn diffusion by Ryan and Gross (1943), and of drug diffusion by Coleman and his colleagues (1966).

Ryan and Gross (1943) laid the groundwork for the social contagion paradigm. They investigated the role of social factors in the decision to adopt a new type of corn seeds by farmers from two rural communities in Iowa. Through surveys, they collected data about farmers' social networks and their socio-economic status, which was used to determine their propensity to adopt the new type of corn. The most prominent finding was that the early adopters were persuaded to switch to new corn seeds by salespeople but in the case of the later adopters, the decision was based upon the exchange of experiences between farmers. In other words, the salespeople were the *source of information*, but other farmers were the dominant *source of influence*. Thus, *interpersonal networks* were a crucial element in the diffusion process (Ryan, B. & Gross, 1943). Social contagion occurred and within few years all farmers in these communities adopted hybrid corn seeds.

The cornerstone of the development of the theory of social contagion was the study of medical innovation diffusion among American doctors (Coleman et al., 1966). Coleman and his colleagues (1966) examined the role played by various links and connections between physicians in the spread of the use of a new drug. They saw that the diffusion processes depended on the *level of integration in the community* and has two distinct features. First, the physicians who were more deeply integrated in the local medical community were more likely to prescribe the new drug. The cumulative process following the S-shaped curve occurred among them. The process was of a contagious nature, comparable to a snowball effect. Second, the adoption advanced at a constant rate among physicians loosely integrated into the community (Coleman et al., 1966). Furthermore, institutional ties, informal professional contacts, and friendships were the factors that played a role in the diffusion process. The diffusion through social contaigon took place in three stages. First, the highly integrated physicians made adoption decision through professional ties; second, the friendship ties became the driver of adoption. Lastly, the isolated physicians adopted the innovation through social influence (Coleman et al., 1966).

To generalize, contagion takes place either through information exchange during interactions between *adopters* and *non-adopters* or through observation of the adoption decision of other agents within a social network. However, contagion is not only driven by the number of subsequent adoptions decisions but also depends on the social structure of the population of potential adopters (Angst et al., 2010). The structure of the social network affects adoption decision in a twofold manner. First, the social proximity between agents is more significant than spatial proximity. The social proximity to the contagion source affects the potency of its influence (Wejnert, 2002). From the perspective of a social network, the actions of agents within the same network are more influential than the actions of actors who do not belong to the same reference group (Greve, 1995). Second, infectiousness depends on the characteristics of the influencer. Some agents are more influential because they are seen by others as models and their behavior is emulated. The agents who are more prominent position will have a higher chance to influence the network. The actors with a high status that control political power or economic resources typically are first to adopt and then impose adoption to the lower status actors (Iyengar et al., 2011; Wejnert, 2002).

Social contagion theory takes a user-centric perspective on innovation diffusion which can be considered a point of critique because it omits the influence of the innovation characteristics on the contagion process. In other words, the implicit assumption of the theory is that the contagion is stimulated only by the users (Langley et al., 2012). This limits the ability of the theory to explain varying adoption patterns of different technologies within the same network.

In sum, in social cognition innovation diffuses in interpersonal networks through interactions between agents and observation of adoption decisions by other agents. Social proximity and the position of agents in the network are two important characteristics of the structure of the system that affect the contagion process.

2.3. International relations: the realist school of thought and diffusion

The realist school of thought in IR is preoccupied with analysis of state behavior and is used to introduce the main concepts relevant in the context of the international state system. Besides, the phenomenon of transnational diffusion also has been observed in the field of IR. Specifically, decisions taken by countries were influenced by the international context. This striking parallel to social contagion asks for further examination.

The following paragraphs introduce and discuss the realist stream and discuss the phenomenon of diffusion in IR.

2.3.1. The realist school of thought

The basic entity in the international system is a *nation-state* that has a defined territory and is ruled by a government accepted by the people living on that territory. For briefness, the nation-state is referred to as ‘state’. A state is considered *sovereign* when there is no external power intervening in its actions within its national borders (Kaufman, 2013). Despite the nuance in meaning, the terms state and country are often used interchangeably. Precisely, country refers to the geographical area and state refers to the political entity exercising its authority over this geographical area. The main limitation of the realist approach lies in the substantive emphasis on state actors. This results in playing down the role of other non-state actors such as international organizations and non-governmental actors.

States are assumed to be monolithic and rational actors pursuing their national interests. *National interests* are all the goals necessary for a state to preserve its essence (Burchill et al., 2013; Kaufman, 2013). The states pursue domestic and foreign policies that align with their national interests. On a critical note, the concept of national interest is elusive and difficult to identify systematically.

International system is a system of identifiable patterns of behavior of states acting towards their national interests (Kaufman, 2013). The structure of the international system arises from the interactions between political actors (Donnelly, 2000).

Especially for realists, power is one of the most critical concepts of IR. *Power* is defined as the ability to influence others through mechanisms of persuasion, encouragement, motivation, or coercion (Kaufman, 2013). The use of power must not be conflictual, countries can exercise influence in the pursuit of national interest through cooperation and negotiation. It is important to stress that the meaning of power is relational, a country can have power over another country. Hence, power is always determined relative terms (Kaufman, 2013).

Realism can be criticized for overemphasizing power. For example, Hans Morgenthau who was one of the most classical scholars of the stream, roots all relationships in power and equates national interest to maximization of power (Morgenthau & Thompson, 1993). Moreover, the concept of power is intangible. For instance, systematic measuring power is almost impossible because of the complexity of the real world (Beckley, 2018; Hart, 1976).

In the sense of structuralist perspective in realism represented by the works of Kenneth Waltz, stability is ensured when there is *balance of power* within the structure of the international system (Donnelly, 2000). Countries enter bi- and multilateral alliances to coordinate their policies, generally for security reasons (Kaufman, 2013). *Alliance* is thus a cooperative treaty agreement between countries that want to aggregate their capabilities and are concerned with national security issues (Salmon, 2006). The creation of alliances assumes that combining powers can offset the domination of other nations and ensure power balance. However, the concept of the alliance also has liberal and constructivist foundations. Apart from security and defense advantages (power maximization), alliances can be pragmatic policy decisions taken by countries with common interests because they can bring other mutual benefits such as increased trade, economic advancement or access to technologies that the countries are not able to produce on their own. The most notable example of power-balancing alliances was formed during the Cold War period: the North Atlantic Treaty Organization (NATO) and Warsaw Treaty Organization anchored by the USA and the USSR (Kaufman, 2013). At the same time, focus on competition between states offers little explanatory power, apart from security reasons, to interpret why countries cooperate, especially when the processes of globalization are considered (Kaufman, 2013). It must be noted that some countries choose to pursue a foreign policy of *neutrality*. This means that they do not commit to military or security alliances and refrain from using their military forces (Kaufman, 2013).

2.3.2. Diffusion in international relations

The concept of diffusion appears in the context of transnational interdependence of decision-making. Decisions made by one country influence domestic change in other countries. An example of diffusion phenomenon in IR is the falling domino effect used to describe the spread of communist regimes (Gilardi, 2012). Pivotal states are those countries that initiate diffusion to their neighbors (Solingen, 2012). The dynamic of the falling domino shares similarities with the process of social contagion described in the previous section. The communist "disease" would spread in different regions through contagious contact (Starr, 1991). Change of political regime is one instance of diffusion process, other politically consequential phenomena such as technologies also can cross borders (Solingen, 2012).

The mechanisms of diffusion can be grouped into four categories: coercion, competition, learning, and emulation (Garrett et al., 2008). In coercion, diffusion occurs through the pressure of other countries; in the case of competition, diffusion occurs when countries aim to attract or retain economic resources (Gilardi, 2012). From the perspective of technology adoption, the most relevant mechanisms seem to be learning and emulation. Learning means that the experiences of other countries inform domestic decisions (Gilardi, 2012) and implies rational decision made by a state (Marsh & Sharman, 2009). Emulation means diffusion through mimicry (Gilardi, 2012), the adoption occurs as a result of copying of behavior of countries perceived as leaders or more advanced (Marsh & Sharman, 2009).

2.4. Comparison of the theories

The diffusion of innovations paradigm can be transferred to other disciplines because it illuminates the diffusion process using a set of generalizable, yet integrated, concepts. In the context of this study, the concepts are bridged to the field of IR. Furthermore, transferring the diffusion of innovations theory to the system composed of countries instead of individuals allows one to overcome some of its limitations. First, the pro-innovation bias is reduced because the selected technologies are investigated while the diffusion is ongoing and the technologies belong to different sectors.

Second, the data about countries can be collected post-hoc from statistical databases. This removed the "recall" problem because the timing of adoption is easy to determine, and the relevant characteristics of the countries were recorded regularly.

The use of a global level of analysis dictates leaving out two aspects of Roger's theory (2003): the steps of innovation generation, and innovation adoption decision. The first aspect is irrelevant because the primary focus is the diffusion of technology among countries, and not how these technologies came about. The latter aspect specifics the stages of attitude formation in the decision-making process. It was left out because does not fit within the scope of this research and it would be practically impossible to collect sufficient data on the decision making process for all technologies and all countires.

Social contagion allows linking the diffusion of innovations paradigm and the realist school of thought in IR because a parallel can be made between the relations between agents in the social networks and the countries constituting the international system. In both theories, the entities interact with each other and occupy different positions in the network. Furthermore, the process of diffusion has been observed in international relations when it comes to policy. Building on these parallels provides a theoretical frame for analyzing the diffusion of technology as a political phenomenon.

Lastly, this research poses a question that requires a political angle and global level of analysis. The preoccupation with macrolevel makes the field of IR relevant for this study because it allows establishing the theoretical base to deal with the international system. In particular, the realist approach to IR is the most suitable for two reasons. First, because it puts states and interdependencies between them at the center of analysis; second, it shares some of the central assumptions with the diffusion of innovations paradigm and the social contagion theory. Furthermore, because the actors in IR are political entities, it provides suitable means for analysis of technology adoption from a political perspective. It must be noted that political realism is not a fixed theory but an approach that has emerged gradually into a distinctive tradition through the work of different scholars (Donnelly, 2000). Realists emphasize the constraints of egoist human nature and the anarchy stemming from the lack of international government. However, treating realism as a theory of international politics allows to shift attention to the structure of international politics (Burchill et al., 2013), which aligns with the focus of this research.

In brief, despite some differences between the discussed theories, there is a substantive level of similarity between the main concepts. Thus, the juxtaposition of these theories allows constructing of an interdisciplinary conceptual framework. The framework draws on complementarities between the theories and can be used for the analysis of the problem stated in the research question. Table 2-1 (next page) presents a summary of the most important comparison points.

Table 2-1 Comparative overview of the theories

	Diffusion of innovations	Social contagion	Realism in IR
Scientific field	Innovation sciences	Behavioral sciences	Political sciences
Level of analysis	Micro, meso	Micro	Macro
Units of analysis	Individuals	Individuals	Nation-states
Network type	Social	Social	Political
Analytical focus	Proliferation of new ideas, practices, or objects	Influence of the relationships between agents on innovation diffusion	Explaining behavior of countries in the international context
Overlaps	• Interdependent agents embedded in networks • Structure of the system influences actions of the agents • Rationality of agents • Presence of diffusion phenomenon		
Core limitation	Focused primarily on the characteristics of the adopting unit	Omitting technology related factors in contagion process	Emphasis on power and competition between states

2.5. Hypotheses

The above theories provide a broad perspective on technology diffusion in the international state system. The literature on social contagion and diffusion in IR suggests several factors on which technology adoption might depend. These factors are expressed in three hypotheses, which will be tested quantitatively (see Figure 2-2).

The parallels between individual agents and national governments as actors within the communities and the international states system allow hypothesizing about how IR affect technology adoption decisions by national governments. Applying the lens of the social contagion to IR allows conceptualizing relationships between individual agents as alliances between countries. Specifically, membership in multilateral alliances indicates a high level of integration in the international system. The allied countries are expected to interact with each other more than with the non-allied countries. Thanks to these interactions the information about the technology can flow through the international state system and the states can influence each other's adoption decisions. Based on these grounds, it is argued that social contagion will occur between allied countries. Thus, the core hypothesis of this study is:

H_1: The more allies of a country adopt a technology the more likely it is that the country will adopt the technology.

The theory of diffusion of innovations posits that adoption is more likely to occur among homophilous individuals because the communication between them is more frequent and more effective. Thus, persons who affiliate with each other tend to share certain attributes (Kandel, 1978). From the perspective of IR, homophily can be linked to diffusion through emulation. The emulation mechanism drives diffusion through mimicry, thus similar countries can be expected to copy each other's behavior when it comes to the adoption of technology. Based on this parallel, it is argued that diffusion through mimicry between similar states will not only apply to policies but also to the technologies they use. Thus, the following hypothesis can be drawn:

H_2: Countries with similar political systems are more likely to adopt the same technologies.

The social contagion theory stipulates that more influential individuals are more contagious and have high a potential to influence their community. Such an ability to influence is a manifestation of power. For instance, powerful, leading countries of an alliance could be able to persuade other countries to adopt certain technologies. As mentioned previously, the use of power does not have to be conflictual. In addition, the diffusion of innovation paradigm indicates that opinion leaders can influence attitudes towards innovation. Thus, the powerful countries can be seen as opinion leaders by their allies, and their diplomats as change agents. Furthermore, the theory of social contagion indicates that innovation is more likely to be adopted by individuals deeply integrated into the community. Therefore, bridging these mechanisms would suggest that the adoption by an alliance leader will have a contagious effect on the other countries of that alliance and that this effect would be weaker in the case of adoption by another alliance member. Hence, the third hypothesis is:

H_3: Adoption of a technology by a leading country in an alliance will have stronger influence on technology adoption than adoption of a technology by a non-leading country in an alliance.

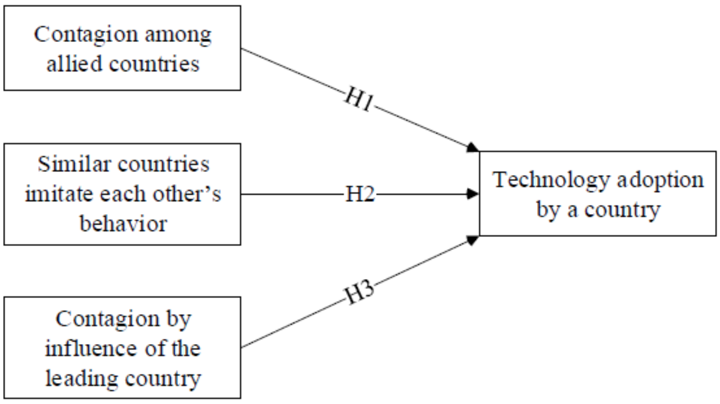

Figure 2-2 Hypothesized factors leading to technology adoption by a country

2.6. Definitions and background information about the technologies

The technologies selected for this study belong to three sectors: energy, transportation, and space. The following paragraphs describe each technology in detail sufficient to understand the issues at hand and to provide contextual information regarding the development of each technology**.** Table 2-2 presents the overview of the selected technologies including invention and innovation years.

Nuclear power

Nuclear power is understood in this study as electricity generated through nuclear fission in a nuclear reactor. Almost 15 percent of the world's energy mix comes from nuclear power. The industry grew until the 1990s and began to decline in the XXI century (Martin, 2020). Most of the nuclear reactors are located in North America, Europe and Asia. Countries typically deploy nuclear power plant if they lack other sources of energy, want to be independent, or desire to reduce pollution and greenhouse gas emissions (Adamantiades & Kessides, 2009). The decreasing prices of nuclear reactors open adoption possibilities for less advanced economies. Nevertheless, nuclear power comes with issues related to safety, high set-up costs, disposal of nuclear waste and proliferation of nuclear weapons (Martin, 2020).

Solar power

The two most common solar power technologies are: photovoltaic panels (PV) and concentrating solar-thermal power (CSP). In PV technology electricity is generated by solar cells which are devices that convert the energy of light to electricity thanks to the photovoltaic effect. Large groupings solar cells can function as electric power plants, smaller arrays can be installed by individual homeowners or integrated into consumer products. PV cells can be integrated into the public utility grids and supplement them in peak times (Ashok, 2020; Fonash & Ashok, 2020). Photovoltaics became a growing industry after the "first oil crisis" of 1973-1974. It took until the turn of millennia for the total installed capacity to reach one gigawatt (Wolfe, 2018a; Wolfe, 2018b). In CSP power plants the electricity is generated using steam turbines that are heated by sunlight. The high temperature needed for steam generation is obtained by collecting sunlight through a system of lenses or mirrors and concentrating it on a single receiver spot (Ashok, 2020). The first trials with concentrated sun took place in the XIX century, with a remarkable example of Augustin Mouchout who used an improved version of his 1866 sun-powered engine to run an ice maker at the 1878 Universal Exhibition in Paris (Ragheb, 2011). After a series of small-scale demonstration projects, the first commercial CSP plant was opened in California in 1984. However, the technology gained real momentum at the beginning of the XXI century (Lovegrove & Stein, 2012).

Wind power

Wind power is defined as the conversion of the kinetic energy of wind into electric energy. It has been used for centuries but in the form known nowadays has been introduced in Denmark in the late 1970s (Owens, 2019). A typical turbine has a blade length of 40m and is attached to an 80m tall tower. Wind farms are large groups of turbines either on land or on offshore locations. The generation of electricity from wind energy has been increasing and reached 4% of the world's energy mix in 2016. The largest producers of wind energy worldwide are China and the United States, with Denmark being the country with the highest share of wind energy in its energy mix. Some challenges to the wide implementation of wind power are related to wind and land availability, aesthetics, and environmental concerns (Eckely Selin, 2020).

Marine power

Marine power entails electricity generation from tides and waves. Tidal power is energy harnessed from ocean tides (Eckley Selin, 2019). There are two variants of the technology: barrage with turbines propelled by waterflow during low and high tides, and tidal fence with turbines taking advantage of ocean current (Collombet, 2020; Eckley Selin, 2019). The first large scale plant was built in France in 1966 (Frau, 1993). Currently, the largest installation with a capacity of 254MW is in South Korea, however, the technology is still in the infancy stage (Boretti, 2020). Wave electricity is generated from the up-and-down movement of ocean waves and has the highest energy density among the renewable energy sources (Clément et al., 2002). There are two common variants: floating turbine platforms and static capture chambers (Britannica, 2018). The first advancements in harnessing wave power can be dated to 1799 (Clément et al., 2002). However, it took over two hundred years until the first modern wave technology power plant began operating in 2008 near the shores of Porto in Portugal (Vosough, 2011).

Higher- and high-speed rail

There is no commonly adopted definition of higher- and high-speed rail because the classification of lines varies from county to country (Akiyama, 2014). The main distinguishing factor is the operating speed. In this study, passenger train service operating at speeds crossing 250km/h is considered high-speed rail (HSR), and higher-speed rail (HRSR) and those services that operate at more than 200km/h but less than 250km/h (Clark Shedd et al., 2020). Besides operating speed, there are crucial technological differences that set HSR and HRSR apart: required infrastructure and rolling stock type. Higher-speed rail operates mostly on upgraded conventional lines with lineside signals and requires lower voltage, technologically it is closer to regular train lines. High-speed rail is built on dedicated special tracks, using locomotives with in-cabin signaling system and requires a voltage of at least 25'000V (Campos, J. & De Rus, 2009). The first operating high-speed networks were introduced in Japan, later the technology has been used in other parts of the world: many European countries, South Korea, China, and Taiwan as leading countries (Clark Shedd et al., 2020; Takatsu, 2007).

Telecommunication satellites

A telecommunication satellite is a system comprising artificial satellites placed on Earth's orbit and ground stations. The satellite receives, processes, and sends signals to a ground station. Typically, telecommunication satellites are used in a point-to-point set-up to transfer data from one antenna to another one that distributes the information to other terrestrial networks (Logsdon, 2020a). Telecommunication satellites enable connecting remote location without extensive ground infrastructure and they can provide a vast range of communication services spanning from telephone calls to internet data to television broadcasting but can also be used during natural disasters and emergencies when land systems are out of service (Labrador, 2020). In 2020, there were about 400 telecommunication satellites orbiting the Earth (Logsdon, 2020).

Meteorological satellites

Meteorological satellites are satellites employed to observe the Earth and collect data used for weather forecasting (Logsdon, 2020b). They came about as a modification of existing technologies after the launch of the first satellites. The first meteorological satellites could observe cloud patterns and serve as a simple warning system. With the advance of instrumentation, the satellites are able to provide rich data about the state of the atmosphere such as temperature, humidity, wind, etc., for example using infrared photography or measurement of microwaves emissions (Gallicchio, 2017). Currently, meteorological satellites are being operated by agencies in China, France, Germany, India, Japan, Korea, the Russian Federation, the United States, in cooperation with the World Meteorological Organisation (OECD, 2014).

Table 2-2 Overview of the studied technologies

Sector	Technology		Invention		Innovation		Country of innovation
			Year	Description	Year	Description	
Energy	Nuclear		1939	discovery of nuclear fission reaction [a]	1954	first reactor connected to the power grid [b]	USSR
	Solar	*PV*	1839	discovery of photovoltaic effect [c]	1983	first utility scale solar PV park [d]	USA
		CSP	1866	demonstration of the first solar collector [e]	1984	first utility scale solar CSP power plant [f]	USA
	Wind		1887	first wind turbine used for electricity generation [g]	1978	first large-scale grid wind turbine [h]	Denmark
	Marine	*Tidal*	1924	study on use of tidal power for electricity generation [i]	1966	first large-scale tidal power plant [j]	France
		Wave	1799	patenting of wave power technique [k]	2008	first commercial wave park [l]	Portugal
Transportation	High- speed rail		1903	first experimental electric train car crosses 200km/h [m]	1964	inauguration of the first line operating above 250km/h [n]	Japan
	Higher-speed rail				1967	opening of the first line operating at 200km/h [o]	France
Space	Telecommunication satellites		1945	concept of placing communication satellite in orbit [p]	1957	launch of Sputnik satellite with radio-transmitter [r]	USSR
	Meteorological satellites		1951	concept of weather observation satellite [s]	1960	launch of TIROS 1 weather satellite [t]	USA

Note. The data was compiled from various sources. Data are from: (Fergusson, 2011)[a], (Rachkov et al., 2014)[b], (Fraas, 2014)[c], (Wolfe, 2018)[d], (Ragheb, 2011), (Lovegrove & Stein, 2012), (Price, 2005)[g], (Owens, 2019)[h], (Al Yusuf et al., 2012)[i], (Frau, 1993)[j], (Clément et al., 2002)[k], (Vosough, 2011)[l], (Mensinger, 2015)[m], (Takatsu, 2007)[n], (Schubert, 2012)[o] (Gille, 2001)[p, r], (Vaughan & Johnson, 1994)[s], (Gallicchio, 2017)[t]

3. Methods

This chapter deals with the analytical framework, it addresses the analytical methods and operationalization of variables used to determine how international relations affect technology diffusion. The study employs statistical analysis of secondary data to assess the generalized relationships posited in 2.5., using the concepts defined in the theory chapter.

3.1. Unit of analysis and population

The unit of analysis in this study is country-technology pair. The analytical framework is built around the international relations of a country and its characteristics as an adoption unit. The focus on international relations dictated omission of the technology-specific factors. Only sovereign states, capable of establishing and maintaining foreign relations, were considered (all dependent territories have been omitted i.e., Hong Kong or Greenland). There was a total of 205 sovereign states identified in the period between 1954 and 2020.

3.2. Data collection

To quantitatively test the hypotheses, a database was constructed. It contains data on technology adoption, international relations, and the relevant control variables reflecting the country's characteristics. It was assembled using secondary data: technology use, historical datasets of international relations, and statistical information about the countries.

The data has been collected by other researchers, statistical institutes, or enthusiasts. Datasets have been selected cautiously. Preference was given to datasets that have been compiled by trustworthy institutions or have been already used in peer-reviewed studies. To assure that the data is of high quality a hierarchical approach to sources selection was taken. The data collected by statistical institutes and other researchers were prioritized over data collected by enthusiasts. Triangulation of sources was applied to ensure the complementarity of the data. Table 3-1 presents the data sources.

3.3. Data preparation

The use of secondary data forced meticulous data preparation. The first step was the analysis of the enclosed codebooks to assure that the data corresponds to the constructs defined in the operationalization step. Because different sources were used, it was necessary to harmonize the country names across the datasets and cross-check the temporal coverage. Furthermore, for certain counties that are known under different names or that have changed their official names, a unique country code identifier has been assigned (see Appendix A).

In the period of observation, some countries merged (i.e., Eastern and Western Germany), split (i.e., Czechoslovakia), or ceased to exist (i.e., USSR). As result, certain nation-states disappeared from the international system or emerged and established relationships with other states.

Because this study analyses relationships between nation-states, these countries were treated as separate entities of the international system in the case of discontinuity. For example, USSR disintegrated in 1991 into fifteen independent republics and Russia being considered a successor state was treated as a new entity. Greater scrutiny was given to such discontinuity cases due to a lack of consistency on how these events were treated by different sources. All cases were examined meticulously in terms of begin and end of statehood to assure that the corresponding data points were assigned to the correct nation-state before inserting them into the database.

Further details about data preparation procedures employed for the specific variables follow in the operationalization section (see 3.5). Such outline is dictated by using secondary data because the variables were iteratively operationalized in the function of the available data. The transparency of the process of linking data with the operationalized variables was necessary to demonstrate the reliability of the methodology.

3.4. Population, sample and observation period

There were 205 sovereign states distinguished between 1954 and 2020, 161 of these were included in the analysis, and 45 countries were excluded from the sample because of a lack of data on the dependent variables. The observation period was adjusted to 1954-2012 because the data on alliances was available up to this year. Appendix A contains the complete list of the countries with official names, country codes, existence period, and comments on exclusion from the study.

For marine power, landlocked countries were excluded from analysis because adoption of the technology is impossible. Additionally, Bosna and Herzegovina, and Jordan were excluded as well because their shoreline is shorter than 30km and judged unfit for large marine power infrastructure.

3.5. Operationalization

The process of operationalization was iterative and was carried out in three stages. First, all relevant constructs have been translated into variables, based upon the theoretical grounds. Second, the secondary datasets have been looked up and assessed for the match between the collected data points and the proposed variables. Third, in the case of lack of an adequate database, the operationalization of a variable was adjusted to better align with the available data. For example, initially, the political regime variable was proposed as a four-level categorical scale but it was changed to a twenty-point continuous scale to harmonize with the best-identified dataset. The following sections describe the variables after the final iteration step. The details of this process are put forth to demonstrate construct validity. All variables are summarized in Table 3-1.

3.5.1. Dependent variable

In this study, the dependent variable is technology adoption *(ADOPTION).* The study takes an extensive adoption margin approach. The variable is thus constructed as a dichotomous variable. Dichotomous variable consists of two categories and the values have no numerical meaning (Salkind, 2010a). The variable takes value 1 if a country has adopted a certain technology at the time of observation, and 0 otherwise. Such construction of the dependent variable allows distinguishing qualitatively between adopters and non-adopter.

Furthermore, the extensive margin research design allows to easily construct databases on the dependent variables (Comin & Mestieri, 2014). Nonetheless, operationalization requires some level of intensity measure to be incorporated. For instance, one demonstration or failed project based on a certain technology does not necessarily mean that the technology has been adopted by a country. The following paragraphs describe the secondary datasets, the intensity of use measure, and cut-off criteria.

The adoption of nuclear power plants was based on the dataset maintained by the IAEA (2020). All reactor types were considered with exception of reactors constructed for research purposes (due to lack of infrastructural character). The reactors with a secondary purpose such as district or process heating were included. A country was considered an adopter if it had at least one power plant, adoption year was set at the year of the grid connection to remain consistent with the previously defined innovation dates.

Solar and wind power data was sourced from EIA datasets on electricity generation (EIA, 2021). They contain aggregated data on: (i) solar PV and thermal collectors from distributed and utility-scale, (ii) wind on- and off-shore. The data included in the EIA dataset were reported by the ministries of energy or statistical offices of the countries. It was impossible to establish an adoption criterion based on installed capacity because no such data was available for the whole observation period. Thus, for solar and wind power a country was considered an adopter when any electricity has been generated using these technologies in a year. Such an approach is considered acceptable because the generation of electricity implies that capacity has been installed and a “reportable” quantity of electricity has been generated.

The data on the adoption of marine power was primarily sourced from the EIA dataset containing aggregated data on electricity generation from tides and waves (EIA, 2021). Contrarily to solar and wind power, a criterion of at least 1MW of installed capacity was established because most reviewed demonstration projects were below that capacity (Tethys, 2021). Additional adoption criterions included the non-experimental character of the projects and grid connection. The technology has not reached maturity and there only a few adopter countries, it was possible to identify single installations thorough review of academic papers and grey literature (see Table 3-1 for the complete list of sources).

The adoption data on higher- and high-speed rail has been principally based on UIC data (UIC, 2020) and complemented by a review of scientific literature on the topic. Countries were considered adopters in the year of the beginning of regular higher- and high-speed services.

Source triangulation was used to determine the adopters of both space technologies: telecommunication and meteorological satellites. The primary data source was the register of the objects launched into outer space kept by the United Nations (UNOOSA, 2021). The classification of mission types (namely: communication and meteorological) was adapted from the General Catalog of Artificial Space Objects (McDowell, 2020). Countries were considered adopters when they had at least one active satellite in orbit. Two additional criteria were developed for the inclusion of satellites in the study. First, the mission had to have either commercial, civil, or defense purpose. Military missions were considered despite doubtful contribution to sustainability goals; however, such launches indicate the use of space technologies. Academic, technology demonstration, and amateur satellites were excluded because they are considered irrelevant from the infrastructural point of view. All multipurpose satellites were considered, even if they had additional functionalities other than telecommunication or meteorology. Second, in the case of joint launches by several countries, every country was deemed an adopter because it could be safely assumed that all counties taking part in the project were also using the services provided by these satellites.

3.5.2. Independent variables

Adoption by the allies

To test the core hypothesis H_1 a variable measuring prior adoption by a country's allies has been constructed. The variable *(ALLY)* is the number of country's allies that have priorly adopted a technology. The international relations data was drawn from the Correlates of War (COW) project (Gibler, 2020). The allies have been identified using a dataset on formal alliances between 1816 and 2012 including defense, entente, neutrality, and non-aggression pacts. In this study, countries were considered allies only when they have signed either a defense or an entente treaty which have lasted at least five years. Defense pacts were selected because they entail the highest level of commitment. Additionally, entente pacts were considered as well even though they are less formal than defense pacts; Nonetheless, previous research showed that this type of treaty indicates the strong bonds between countries (Krause & Singer, 2001). The neutrality and non-aggression pacts were considered irrelevant because the signatories merely pledged to refrain from using military force. Furthermore, it has been noted that frequently such treaties were singed off by countries after a settlement of a military dispute. The 5-year limit of minimal alliance duration was set to exclude temporary and less institutionalized commitments. Appendix B contains the complete list of the identified alliances, including alliance type, begin and end dates as well as the member states.

Similarity of the political system

The similarity of the political systems was established using Polity V dataset (Marshall, 2020). The dataset was designed for longitudinal analysis of political regimes characteristics and transitions between 1800 and 2018, for countries with a population over 500’000 inhabitants in 2006. Marshall and Gurr (2020) defined polity as institutionalized patterns characterizing the formal political or government organization within a state. The dataset includes measures of institutionalized democracy and autocracy combined in a single score of polity, where +10 denotes full democracy and -10 denotes full autocracy. The scores are based on three dimensions of the political systems: executive recruitment, the independence of executive authority, and political competition and opposition (Marshall & Gurr, 2020).

For hypothesis testing, it was necessary to establish political similarity to adopters. Thus, the variable measuring the similarity of the political systems was constructed as the sum of the absolute differences of polity score of a country and all adopter countries in a given year. A low value of this sum indicates high similarity between states and a high value indicates low similarity. To facilitate interpretation, the variable was named *(DISSIMILARITY).*

Adoption by the leader

Power can serve as a basis to define a leader among countries. It can be implied that the most powerful country will also be the leader because it will have the ability to shape the politics and align it with its interests (Beckley, 2018). The intangibility of power makes it difficult to measure. However, some proxies can be used when the concept is broken down into hard and soft power. Hard power is represented by military and economic strength while soft power is demonstrated by the ability to shape the agenda, for example, through diplomatic missions (Nye, 2003). While hard power is more tangible and easier to measure, soft power is indirect and difficult to quantify. For example, a country can exercise soft power if other countries follow willingly the trends established by the leading country (Nye, 2003). Thus, because of the quantitative approach, only hard power was operationalized in the study.

The third hypothesis required constructing two dependent variables. First, the leader *(LEADER)* among allies of a country has been determined as the country that has the highest power. If the leader has adopted a technology the variable took value 1, and 0 otherwise. If the country itself was the most powerful ally, the variable was assigned value 0. Second, to compare the influence of adoption by a non-leading country, a *(NON-LEADER)* variable was constructed. It took value 1 if at least one of the country’s allies that was not the leader has adopted technology, and 0 otherwise.

The leader was defined based on the Composite Indicator of National Capability (CINC). The indicator is an aggregate measure of military expenditure, troops, population, population, iron and steel production, and consumption of energy (Beckley, 2018). It is an indication of a country's relative power at a global level. However, the CINC must be used with precaution because it exaggerates the power of less developed and populous countries (Beckley, 2018). The CINC also captures the economic power indirectly through the consumption of energy because of the energy consumption-economic growth nexus (Ozturk, 2010).

3.5.3. Control variables

Control variables are derived from the characteristics of the country that might affect the technology adoption decision. They are introduced to guard against potential confounders in the relationships posited in the theoretical part of this study and were proposed based on the extensive review of literature on technology adoption determinants.

Adoption by the neighboring countries

The spatial proximity between countries can influence adoption decision. For example, in the case of transportation technologies, attractiveness of the technology increases if a neighbor country has adopted it. Geographical proximity facilitates knowledge transfer and learning (Omobhude & Chen, 2019). For instance, if a technologically forerunning country in the region develops renewable energy plants the neighboring countries can gain knowledge about it and decide to adopt the same technology (Fadly & Fontes, 2019). The variable reflecting adoption by the neighboring countries *(NEIGHBOR)* is the number of country's neighbors that have adopted technology.

The information about neighboring counties was taken from the dataset on direct contiguity between states from 1816 through 2016 maintained by the COW project (Stinnett et al., 2017). The dataset contains five types of contiguity: one for land or river borer, and four for water contiguity (12, 24, 150 and 400 miles). Countries were considered neighbors when they had a land border or water if the distance was between the shorelines was less than 24 miles. The distance of 24 miles was selected because it reflects the overlap of territorial waters limits of 12 miles (Hensel, 2017).

Government size

High government spending can lead to inefficiencies of the institutions because of the increasing regulatory complexity, uncertainties, and bureaucracy (Caselli & Coleman, 2001; Galang, 2012; Hauner & Kyobe, 2010; Karras, 1997). Such circumstances can be detrimental to international technology adoption as exemplified by the slow adoption of electronic ticketing systems and computers in some countries (Caselli & Coleman, 2001; Galang, 2012). Conversely, well-funded governments have sufficient means and are suitable actors to carry out the complex, large infrastructural projects. A large public sector can have a positive impact on the adoption of the technologies analyzed in this study (Di Matteo, 2013). Thus, government size was judged an appropriate control variable.

The government size variable (GOV_SIZE) is constructed as the share of government spending in gross domestic product (GDP). The data has been sourced from the World Bank (2020a) dataset with temporal coverage from 1960 to 2020.

Human capital

Human capital facilitates the adoption of new technologies transferred from abroad (Sarkar, 2007). Lack of human capital hinders adoption because of skills shortage (Lee, 2001). Highly advanced technologies once adopted must also be operated by qualified personnel. Similarly, the implementation of a large infrastructural project requires a sufficient level of domestic know-how. High education level is associated with high skills level (Hall & Khan, 2003). Weak human capital creates an adoption barrier. Human capital *(HUMAN_CAP)* is thus a variable that measures the ability of a country to deal with complex technologies.

The most extensive statistics on education have been collected by UIS (2020) providing internationally comparable data on mean years of schooling, attainment, and enrollment rates. To avoid multicollinearity issues gross enrollment rates (primary to tertiary) were selected because of the highest number of data points available.

Domestic industry strength

Countries with a strong industrial base can be expected to be forerunners in technology adoption. First, because they have the technological capacity to develop new solutions. Second, should be more likely to adopt external knowledge to their ends thanks to absorptive capacity. Absorptive capacity is the ability to evaluate and utilize external knowledge, it is positively correlated to prior knowledge (Cohen, W. & Levinthal, 1990). While initially developed in the field of organizational studies, the concept of absorptive ability can also be applied to countries. Studies have shown that countries with high levels of prior knowledge a have higher absorptive capacity (Filippetti et al., 2017). Thus, a country's domestic industry strength and innovative output can be proxied through patent statistics (Kim, J. & Lee, 2015).

The number of patents *(PATENTS)* was chosen as an indicator of the technological strength of countries (Dubarić et al., 2011; Pilkington et al., 2002). The data was sourced from the United States Patent and Trademark Office (USPAT, 2015). The number of utility patent filed by geographical area has been selected for two reasons. First, utility patents represent inventions and discoveries of new technological products or processes; second, patent filing statistics reflect the degree of innovative activities (while patent grant only reflects when a patent has been approved by the authority). The total number of patents has been transformed using the binary logarithm of the total number of patents. Analytically, this means that the influence of the doubling of the number of patents will be examined (ref. to 3.7.1 for the explanation).

Nonetheless, a few critical remarks must be made about using patent statistics. First, the USPTO data is best suited for global analysis because it contains a high number of international patents (Criscuolo, 2006; Kim & Lee, 2015) but at the same time it overrepresents American patents. The reason for that is that the highest number of applicants is from the USA because the office also serves as a national patent authority. Second, all patent classification types were included because not all studied technologies could be mapped easily to a single classification category. Third, the simple count of patents does not show how valuable a patent is (Trajtenberg, 1990); nonetheless, constructing more advanced patent indicators, i.e., based on citation analysis (Karki, 1997) would go beyond the scope of this study. Fourth, the patent counts may not represent adequately the strength of domestic industry because not all innovative output is patentable and patented.

Trade openness

Trade openness can positively affect technology adoption, especially in the case of trade with more technologically advanced partners. Trade openness is also related to learning effects through knowledge transfer and spillovers that enhance the capability of adoption (Amidi & Fagheh Majidi, 2020; Hall & Khan, 2003). Technology is adopted through the trade push effect (Comin & Hobijn, 2004; Comin & Mestieri, 2014). Moreover, trade openness diminishes resistance toward new technologies (Parente & Prescott, 1994). Trade levels offer a measure of the extent of the economical connectedness of the country with the rest of the world (Corrales & Westhoff, 2006). Trade openness (*TRADE*) is measured as the sum of a country's imports and exports expressed as the percentage of its GDP. The data was sourced from the World Bank (2020c) for the period between 1960 and 2019.

Political stability

Carrying out a large infrastructural project is a long-term endeavor. For example, setting up a nuclear power plant can take up to 25 years (Thurner et al., 2014). Such long temporal scope exceeds the length of political terms in many countries. Frequent changes in the political systems can adversely impact the adoption as decision-makers are more likely to think in a short-term perspective and may also reverse previous adoption intentions by their predecessors (Aisen & Veiga, 2013). Thus, the political stability variable *(STABILITY)* controls for the effects of the uncertain and volatile political landscapes of the country.

The political stability has been adapted from the Polity V project (Marshall & Gurr, 2020). It reflects the regime stability and is operationalized as the number of years since the most recent regime change. The regime change is understood as a change of polity score by at least three points in a period up to three years or the end of a period without stable political institutions. Notably, coups d'état either violent or not, are not considered as a change of regime as long as they are not associated with a change of regime characteristics. This institutional point of view can be perceived as a shortcoming of this variable. Ideally, the effects of severe changes such as coups d'état or political assassinations should be considered in the variable construction (Campos, N. & Nugent, 2002).

Political regime

Previous studies have also shown interactions between technology characteristics and the type of political regime. For instance, the case of information technologies shows that authoritarian states favor television over the internet because the content can be better controlled to protect the political interests of the regime (Corrales & Westhoff, 2006). Comin and Hobijn (2004) have also found that concentration of political power in the military can slow down the adoption of technology in a country. Conversely, democratic societies tend to adopt earlier because the interests of different groups are considered (Comin & Hobijn, 2004).

In brief, the political regime is understood as a configuration of political institutions (Schmitter, 2016). The variable *(REGIME)* was adapted from the Polity V database and corresponds to the polity score of the country (Marshall & Gurr, 2020).

Investment capability

The adoption of large infrastructural technologies entails substantial investment. Prosperous countries can be expected to have a higher capability to finance such projects (Comin & Hobijn, 2004). Investment capability *(INVEST)* is proxied through the country's GDP per capita to control for the relative wealth of countries regardless of their populations. The data on GDP per capita was sourced from the World Bank (2020b). It was decided to perform the binary logarithmic transformation of these values because the GDP can take remarkably low or high values and the estimated logistic regression coefficients correspond to the difference log odds when the predictor differs by unit (Hosmer et al., 2013). Therefore, one unit change in the value of the binary logarithm of GDP per capita corresponds to doubling of a country's GDP per capita. From the analytical point of view, the influence of the doubling of a country's GDP per capita is more sensible to interpret than the influence of increase by one monetary unit (refer to 3.7.1 for the explanation).

Surface area

Certain of the studied technologies require a significant amount of land. For example, solar parks can take up to 2.2 hectares per 1MW of installed capacity (Lumby, 2015), potentially leading to land-use conflicts in smaller countries. Similarly, high-speed rail is only sensible in countries with great distances between urban centers. Thus, a control variable reflecting the county's surface area *(SURFACE)* was introduced, the increasing country's size should show positive effect on technology adoption. The data was sourced from FAO (2020).

3.5.4. Time effects and adoption lags

The dataset corroborated for this study is a cross-sectional time-series set. Time effects must be accounted for because there are multiple observations of variables for each country-technology pair across the time range. The concept of adoption lag allows to include these effects in the model. Adoption lag is understood as the delay between the first use of a given technology by any county in the world and the adoption of it by another country. With the proliferation of technologies knowledge about them disseminates globally. Thus, time is expected have a positive impact on adoption. The time lag variable (*TIME_LAG*) is constructed for each technology and is measured as the number of years since the first use by a country.

Table 3-1 *Variables and data*

Concept	Variable	Measurement	Description and codes	Data sources	Temporal coverage	Number of countries
Dependent variables						
Technology adoption	ADOPTION	Categorical	1: country has adopted the technology 0: country has not adopted the technology	Nuclear power: (IAEA, 2020)	1954-2019	205
				Solar power: (EIA, 2021)	1980-2019	195
				Wind power: (EIA, 2021)	1980-2019	195
				Marine power: (Charlier & Finkl, 2009), (Chowdhury et al., 2020), (EIA, 2021), (Falcão et al., 2020), (Fedorov & Shilin, 2010), (Greaves & Iglesias, 2018), (IRENA, 2019), (Jacobson et al., 2017), (Kim, G. et al., 2012), (Leijon et al., 2008), (Mikladal, 2008), (Narula, 2019), (Pecher et al., 2011), (Savidge et al., 2014), (Tethys, 2021), (Wang, Z. J. & Wang, 2019)	1980-2019	195
				Higher-speed rail: (Akiyama, 2014), (Amos et al., 2010), (Barrow, 2019), (Bouley, 1994), (Chou et al., 2014), (Dilshod et al., 2018), (Engelhardt, 2019), (Gieras, 1995), (Givoni, 2006), (Hove, 2000), (Hughes, 2006), (Massel, 2018), (Melibaeva, 2010), (Narvesen, 1999), (Popov & Chowdhury, 2016), (Stripple & Uppenberg, 2010), (UIC, 2020), (Westwood, 2002), (Zhou & Shen, 2011)	1964-2019	205
				High-speed rail: ibidem	1964-2019	205
				Telecommunication satellites: (ASCR, 2012), (McDowell, 2020), (NASA, 2021), (UNOOSA, 2021)	1960-2019	205
				Meteorological satellites: ibidem	1960-2019	205
Independent variables						
Prior adoption by allies	ALLY	Continuous	The count of country's allies that have adopted a technology	Derived from the dataset of formal alliances between countries: (Gibler, 2020)	1816-2012	167
Similarity of political system	DISSIMILARITY	Continuous	The sum of absolute differences of Polity scores between a country and all adopters	Derived from the dataset of political regimes Polity V: (Marshall, 2020)	1800-2018	178
Adoption by the leader	LEADER	Categorical	1: the leader has adopted a technology	Derived from the dataset of the Composite Indicator of National Capability: (Singer et al., 2017)	1816-2012	205

Concept	Variable	Measurement	Description and codes	Data sources	Temporal coverage	Number of countries
Adoption by a non-leader country	NON-LEADER	Categorical	0: the leader has not adopted a technology 1: a non-leader has adopted a technology 0: none of the non-leader allies has adopted a technology	Derived from the dataset of the Composite Indicator of National Capability: (Singer et al., 2017)	1816-2012	205
			Control variables			
Adoption by neighbor	NEIGHBOR	Continuous	The count of country's neighbors that have adopted a technology	Derived from the dataset of sea and land borders between countries: (Stinnett et al., 2017)	1816-2016	205
Government size	GOV_SIZE	Continuous	The government spending expressed as share of country's GDP (%)	Dataset on government spending: (World Bank, 2020a)	1960-2020	194
Human capital	HUMAN_CAP	Continuous	The gross enrollment ratio, primary to tertiary education, both sexes (%)	Dataset on enrolment ratios: (UIS, 2020)	1970-2020	195
Domestic industry strength	PATENTS	Continuous	The log transformed number of patents filed by inventors from a country	Derived from the patent application dataset: (USPAT, 2015)	1965-2015	181
Trade openness	TRADE	Continuous	The sum of exports and imports expressed as share of country's GDP (%)	Dataset on trade openness: (World Bank, 2020c)	1960-2019	194
Political stability	STABILITY	Continuous	The numbers of years since the most recent regime change	Derived from the dataset on political regimes Polity V: (Marshall, 2020)	1800-2018	178
Political regime	REGIME	Continuous	The Polity score, ranging from -10 for full autocracy to 10 for full democracy	Dataset on political regimes Polity V: (Marshall, 2020)	1800-2018	178
Investment capability	INVEST	Continuous	The log transformed country's GDP per capita	Derived from the dataset on GDP per capita: (World Bank, 2020b)	1960-2019	195
Surface area	SURFACE	Continuous	The country's surface in thousands of km^2	Dataset on country surface area: (FAO, 2020)	1961-2018	198
Time lag	TIME_LAG	Continuous	The number of years since a technology has been adopted by the first country	Derived from Table 2-2	1954-2020	174

3.6. Logistic regression

The following paragraphs describe the key concepts in logistic regression and model quality criteria.

3.7.1. Key concepts

Logistic regression is a suitable analysis tool when the dependent variable is dichotomous. (Pennings, 2016; Salkind, 2010b). It is a type of generalized linear model (GLM) and allows finding the best fitting and the most parsimonious model of the studied relationship. In addition, it is suitable for assessing the impact of each variable on the adoption probability (Bartoloni & Baussola, 2001; Hosmer et al., 2013). Furthermore, confounding factors can be included in the model (Tolles & Meurer, 2016).

The equation of the logistic regression model is (Salkind, 2010):

$$logit(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_i X_i \tag{1}$$

Where:

- Y is the dependent variable,
- $logit(Y)$ is the natural logarithm of the odds of Y,
- i is the number of independent variables X_i,
- β_i is the coefficient associated with the independent variable X_i,
- α is a constant intercept.

The value of $logit(Y)$ equals the value of the intercept α when all the independent variables X_K are equal to zero.

The dependent variable can take value 1 or 0. P_1 and P_0 are the probabilities of the dependent variable taking value 1 and 0, respectively. Because there are two possible outcomes the probability theory implies that (Salkind, 2010):

$$P_0 = 1 - P_1 \tag{2}$$

The odds are defined as the probability that an event will occur dived by the probability that an event will not occur (Tolles & Meurer, 2016). Thus, the odds of the dependent variable taking value 1 are (Salkind, 2010):

$$\frac{P_1}{P_0} = \frac{P_1}{1 - P_1} \tag{3}$$

The natural logarithm of the odds is the logit of the probability. Thus, $logit(Y)$ equals to the natural logarithm of the odds (Salkind, 2010):

$$logit(Y) = \ln\left(\frac{P_1}{1 - P_1}\right) \tag{4}$$

The odds ratio e^{β} is used in the interpretation of the logistic regression coefficients. The odds ratio is the change of odds resulting from a 1-unit change in the independent variable, all other variables remaining constant (Field, 2013). Thus, if the odds ratio is greater than 1 it means that the odds of the outcome increase as the independent variable increase by 1 unit. This has an important implication for the interpretation of the variables transformed using the binary logarithm (logarithm to the base 2) because the 1 unit increase of the log-transformed variable corresponds to the doubling of the untransformed data. This means that positive coefficients associated with the transformed data should be interpreted as the influence of a twofold increase of their untransformed values.

3.7.2. Measures of model quality

Log-likelihood

Log-likelihood statistic is a measure of the goodness of fit of the model, it is an indicator of how much unexplained information there is in the model. Large values of log-likelihood indicate a poor fit of the model (Field, 2013).

Deviance and Omnibus test of model coefficients

Model deviance D (or $-2LL$) is expressed as:

$$D = -2 \times log - likelihood \tag{5}$$

It is a better tool to compare models because it has a chi-square distribution that allows calculating the significance (Field, 2013). In Omnibus tests the improvement of the model is expressed as the difference of deviance between the new model and the baseline model:

$$\begin{gathered} \chi^2 = D_{new} - D_{baseline} \\ d_f = k_{new} - k_{baseline} \end{gathered} \tag{6}$$

The degree of freedom d_f is the difference between the number of parameters k of the new model and the baseline model.

Pseudo-R^2

Model fit can be further assessed using a pseudo-R^2, which can be conceptually related to R^2 in linear regression and indicates how much variance in the outcome is explained by the model (Field, 2013).

This study uses Nagelkere's measure R_N^2:

$$R_N^2 = \frac{1 - e^{\left(\frac{(-2LL_{new}) - (-2LL_{baseline})}{n}\right)}}{1 - e^{\left(-\frac{-2LL_{baseline}}{n}\right)}} \quad (7)$$

where n is the sample size (Field, 2013).

Hosmer-Lemeshow test

It evaluates if the null hypothesis that the model is a good fit for the data. Thus, for a model with a good fit this test should be insignificant.

Other tools commonly used measures for model quality are receiver operating characteristic (ROC) analysis and classification tables. However, these checks can be skipped in this research because they are more relevant for models built with the purpose of case classification based on the predicted probability of falling to a category (Hosmer et al., 2013; IBM, 2019).

3.7.3. Testing assumptions

Verifying the assumptions before executing regression is crucial to assure that the logistic model yields accurate results (Josephat & Ame, 2018). The assumptions are listed in Appendix G.

Linearity of the logit

The assumption of the linear relationship between the continuous predictors and the logit can be verified with the help of Box-Tidwell test. In this approach, the interaction terms between independent variables X_i and their natural logarithm transformations $ln(X_i)$ are added to the model. Statistical significance of these term suggests non-linearity issues (Ryan, T., 2009).

Collinearity and multicollinearity

Collinearity between variables be can verified through the assessment of the correlation matrix. High correlations (above *.80*) can signal multicollinearity issues. The following criteria for multicollinearity diagnostics have been adopted (Field, 2013):

- variance inflection factor (VIF):
  - the average substantially greater than 1 indicates a potential bias,
  - the maximum greater than 2.5 indicates minor concern,
  - the maximum greater than 10 indicates major concern,
- tolerance:
  - below 0.2 indicates a potential problem,
  - below 0.1 indicates a serious problem.

3.8. Research design quality

To assure research quality, these three criteria shall be considered: reliability, replication, and validity (Bryman, 2012). First, the reliability is expected to be of minor concern because the measured constructs are stable over time. However, using different data sources could impact the consistency of the results. Second, the research process has been described in detail and the datasets have been referenced to assure replicability of this study. Lastly, the validity can be further broken down to measurement, internal and external validity (Bryman, 2012). Operationalization of the concepts has been backed up with relevant theories and carried out in line with other quantitative studies on technology adoption. Furthermore, the approach has been reviewed by the supervisor of this thesis and his feedback has been considered. In terms of assuring internal validity, the hypothesized relationships have been inferred from theoretical ideas and control variables have been introduced to exclude extraneous factors. The results are expected to have external validity because the selected sample contains the majority of the countries comprising the international state system.

4. Results

The results are presented as follows. First, the data is presented through descriptive statistics and adoption curves. Second, the logistic assumptions are tested. Lastly, the four regression models are compared, and the results are introduced. The analysis has been carried out using SPSS 26 software package.

4.1. Descriptive statistics

The descriptive statistics are shown to introduce the data and characterize the sample. The dependent and independent variables are presented separately because they differ per technology. The control variables, with the exception of the neighbor effect, were used for all technologies and are discussed separately.

4.1.1. Dependent variable

Table 4-1 presents the descriptive statistics of technology adoption variable (ADOPTION). Because the data is a time series, it is more reasonable to draw conclusions from the graphs of the cumulative number of adopter countries over time. The data is presented as follows:

- Each technology plotted separately with scaled axes to show the diffusion of each technology in a close-up (Figure 4-1, page 49 and 50),
- Technologies grouped per sector to demonstrate the big picture of sectoral developments and bring forth the differences in diffusion patterns across technologies (Figure 4-2, page 51).

Table 4-1 Dependent variables descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
ADOPTION					
Nuclear power	7772	0	1	.16	-
Solar power	4215	0	1	.23	-
Wind power	5029	0	1	.23	-
Marine power	5294	0	1	.03	-
High speed rail	6784	0	1	.03	-
Higher speed rail	6784	0	1	.07	-
Telecommunication satellites	7218	0	1	.21	-
Meteorological satellites	7218	0	1	.09	-

Figure 4-1 and Figure 4-2 show that the use of each technology has increased over time, all curves follow the S-shape. There are a few interesting observations. First, the S-curve of nuclear power seems to have reached its asymptote in the 1990s when the other three energy technologies started to diffuse, some countries discontinued the use of nuclear power technology. Second, solar and wind power are the most widespread with over 100 adopter countries, the adoption pattern almost perfectly follows the theoretical S-curve. Third, the plot of the marine power indicates the infant phase of the technological development, there were only three adopter countries since the beginning of diffusion in 1966 until 1999 (namely: Canada, France and USSR, using tidal power plants). Evidently, there was a technological breakthrough in the year 2000 exhibited by a sudden increase in the number of adopters, which can be explained by the commercialization boom of the wave power plants (refer to technology descriptions in 2.6). Fourth, both higher- and high-speed rail are adopted by around less than three dozen countries: 25 adopters of higher-speed rail and 20 adopters of high-speed rail. When both diffusion curves are plotted in one graph, the technological "race" becomes apparent. Few countries responded to the Japanese Shinkansen by upgrading their lines to higher-speed, but it took until 1981 for France to develop and start using the state-of-the-art high-speed rail (the TGV network). The slopes of higher- and high-speed rail suggest that both technologies are in the take-off phase. Lastly, both space technologies had a sudden increase of adopters in the 1980s which can be explained by international launches. Interestingly, much fewer countries use meteorological satellites than telecommunication satellites.

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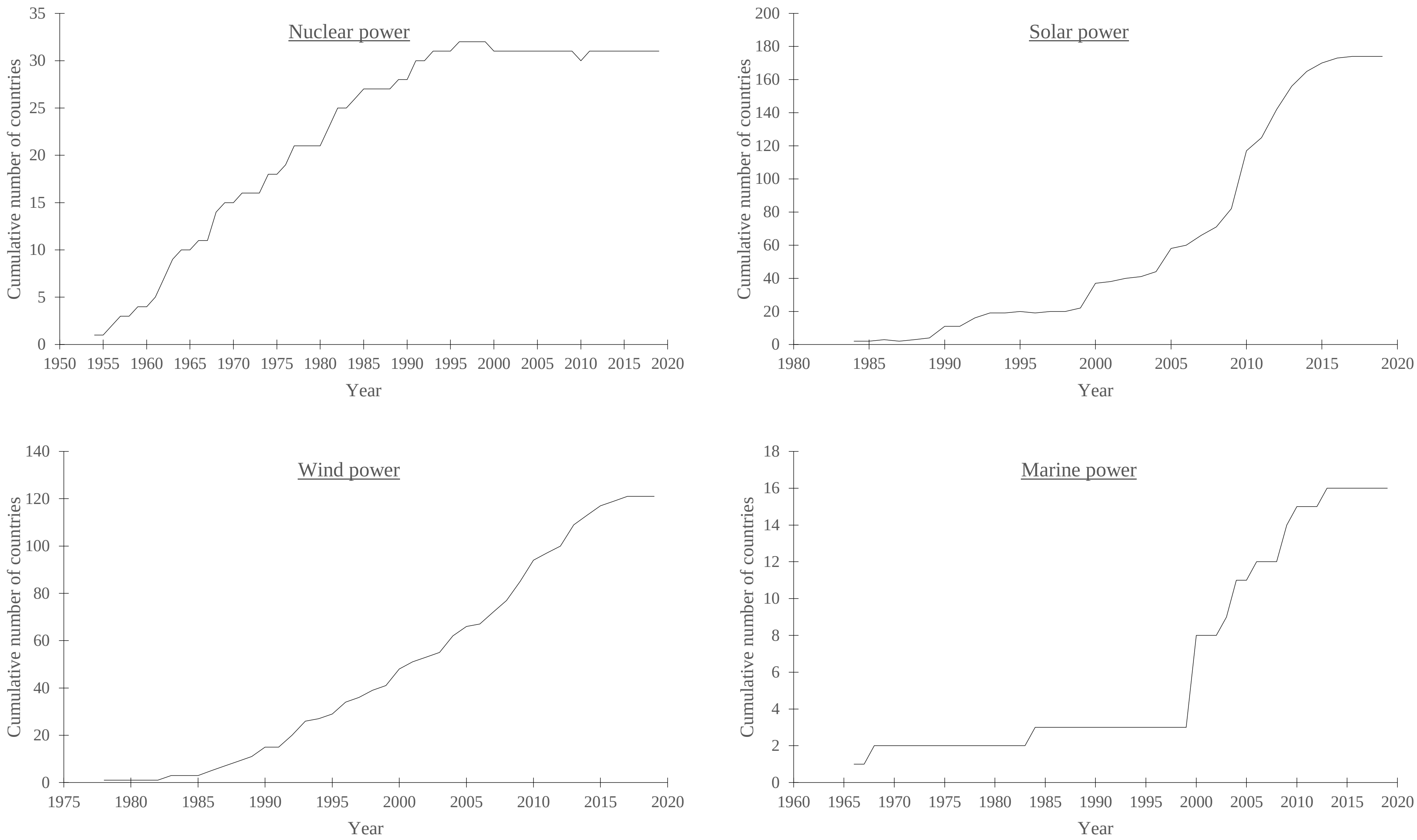

Figure 4-1 Adoption curves

Note: the figure continues on the next page

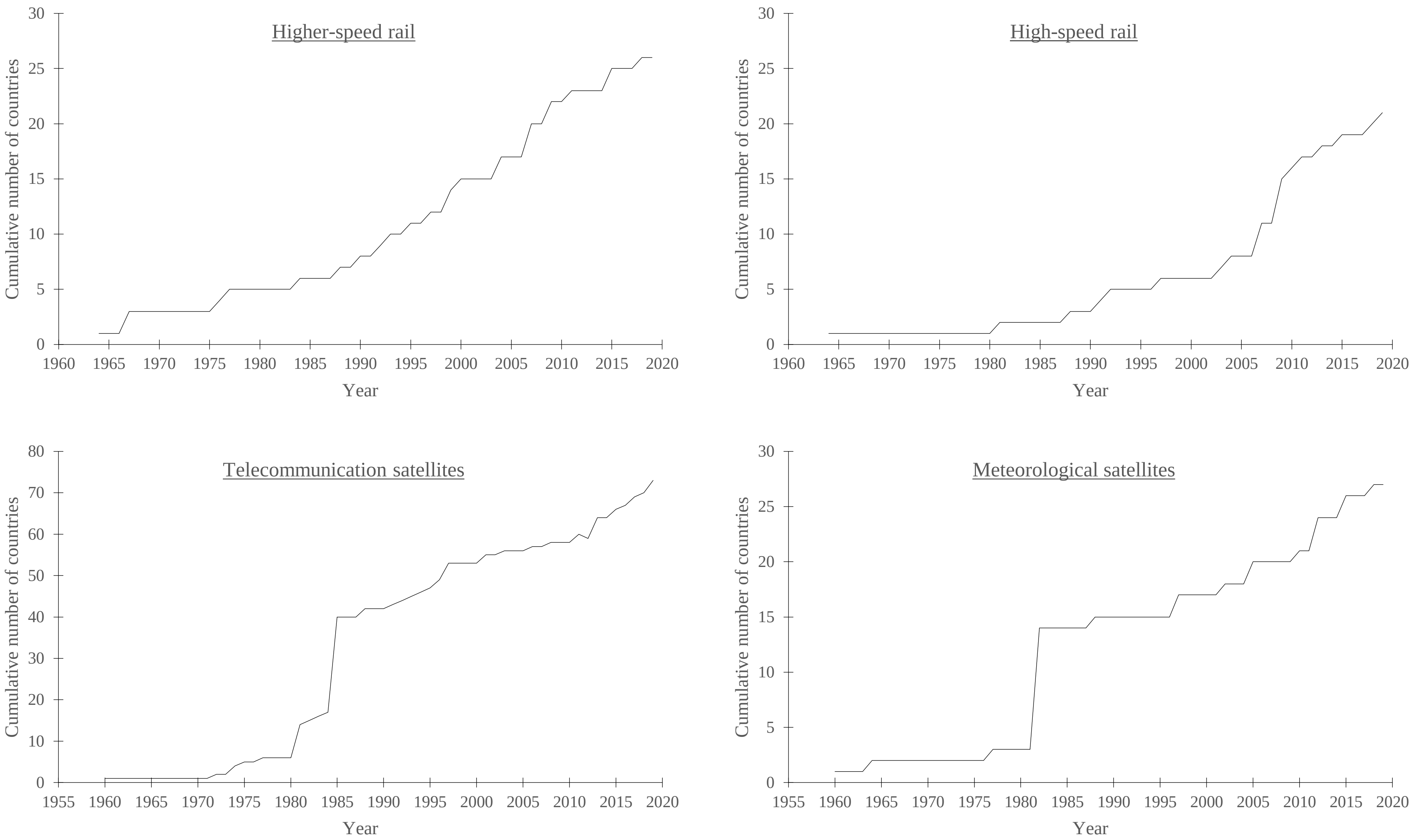

Figure 4-1 (cont’d) Adoption curves

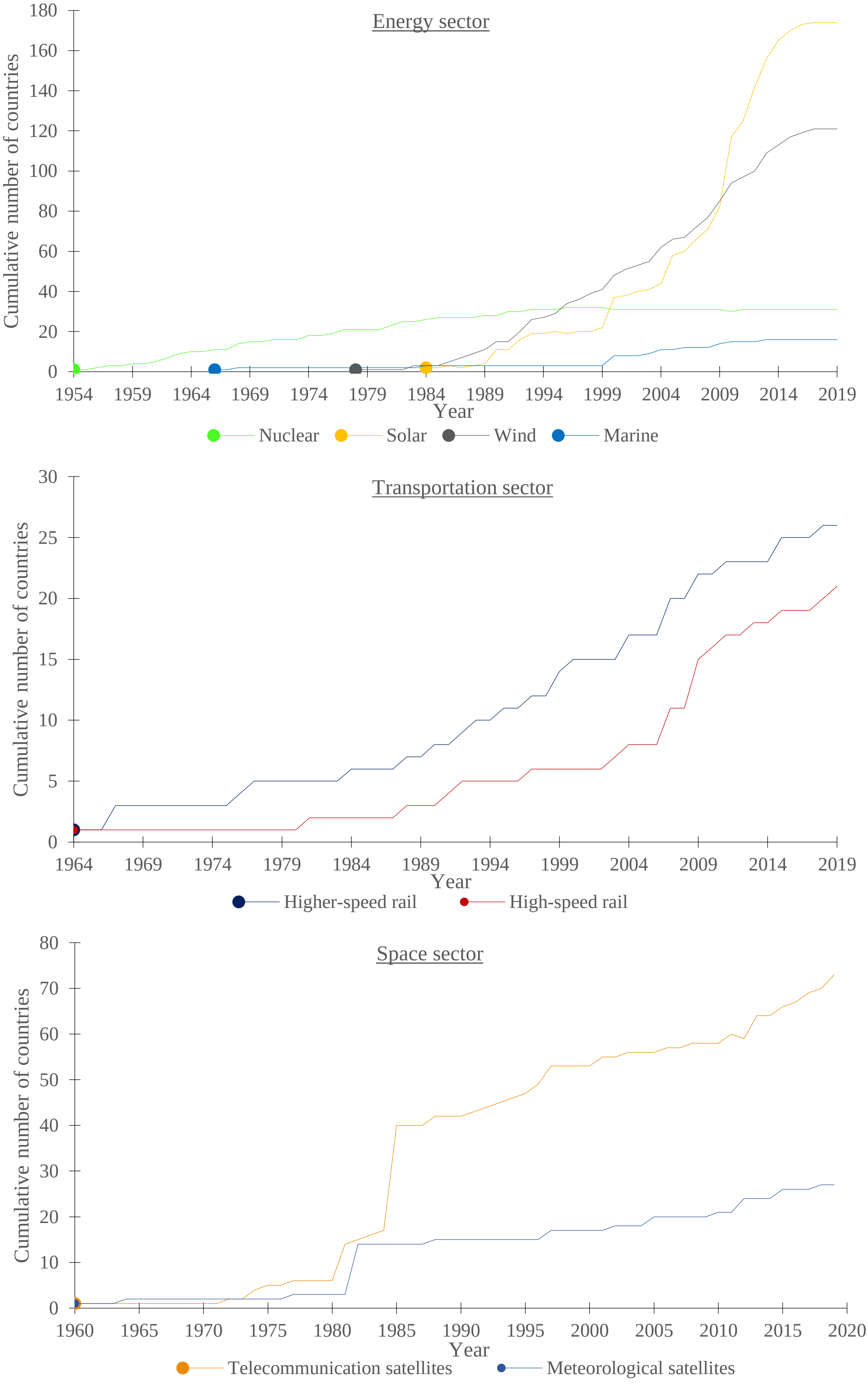

Figure 4-2 Adoption curves per technological sector

4.1.2. Independent variables

The independent variables are presented in Table 4-2. There are fewer observations for the similarity of the political system variable compared to the other three independent variables due to the missing scores in the Polity dataset. In general, the more widespread technologies have a higher number of prior adoptions by the allies, which seems to be a natural consequence of diffusion. Interestingly, the comparison of the mean values of adoption by the leader and non-leader does not indicate any distinct pattern across the technologies.

Table 4-2 Independent variables descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
ALLY					
Nuclear power	7772	0	20	1.92	3.370
Solar power	4245	0	53	3.41	6.123
Wind power	5043	0	46	3.55	6.405
Marine power	5368	0	7	.43	.940
High speed rail	6784	0	10	.43	1.471
Higher speed rail	6784	0	13	1.06	2.371
Telecommunication satellites	7218	0	22	3.28	5.821
Meteorological satellites	7218	0	18	1.41	3.175
DISSIMILARITY					
Nuclear power	7635	0	554	178.72	130.567
Solar power	4168	0	1822	252.80	265.356
Wind power	4625	0	1415	251.45	263.293
Marine power	5294	0	154	23.70	16.675
High speed rail	6670	0	272	35.14	43.056
Higher speed rail	6670	0	392	73.97	74.976
Telecommunication satellites	7098	0	819	244.47	185.179
Meteorological satellites	7098	0	509	102.81	115.963
LEADER					
Nuclear power	7772	0	1	.43	-
Solar power	4245	0	1	.37	-
Wind power	5043	0	1	.34	-
Marine power	5368	0	1	.03	-
High speed rail	6784	0	1	.02	-
Higher speed rail	6784	0	1	.38	-
Telecommunication satellites	7218	0	1	.49	-
Meteorological satellites	7218	0	1	.42	-
NON-LEADER					
Nuclear power	7772	0	1	.33	-
Solar power	4245	0	1	.40	-
Wind power	5043	0	1	.46	-
Marine power	5368	0	1	.24	-
High speed rail	6784	0	1	.10	-
Higher speed rail	6784	0	1	.14	-
Telecommunication satellites	7218	0	1	.34	-
Meteorological satellites	7218	0	1	.20	-

4.1.3. Control variables

The control variables have been collected for the whole observation period and for all countries in the sample. In general, the least data points were available at the beginning of the observation period and for less developed countries (see Table 4-3).

Table 4-3 Control variables descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
NEIGHBOR					
Nuclear power	7772	0	7	.69	1.156
Solar power	4245	0	13	.86	1.422
Wind power	5043	0	16	.88	1.520
Marine power	5368	0	3	.12	.345
High-speed rail	6784	0	6	.13	.500
Higher-speed rail	6784	0	6	.30	.741
Telecommunication satellites	7218	0	9	.86	1.332
Meteorological satellites	7218	0	9	.40	.923
STABILITY	7712	0	203	21.65	28.349
REGIME	7635	-10	10	.54	7.447
TIME_LAG					
Nuclear power	7772	0	58	31.48	16.468
Solar power	4245	0	28	14.35	8.269
Wind power	5043	0	34	17.52	10.023
Marine power	5368	0	46	23.64	13.439
High-speed rail	6784	0	48	25.15	14.020
Higher-speed rail	6784	0	48	25.15	14.020
Telecommunication satellites	7218	0	52	27.49	15.096
Meteorological satellites	7218	0	52	27.49	15.096
PATENTS	6221	.00	18.04	3.133	4.056
TRADE	5638	.02	437.33	68.170	45.973
INVEST	6308	5.23	16.82	10.597	2.395
SURFRACE	6881	.68	22412.37	956.135	2432.228
GOV_SIZE	1596	3.43	210.21	22.851	10.567
HUMAN_CAP	3440	4.45	115.34	64.465	21.025

4.2. Analysis of the assumptions

4.3.1. Linearity of the logit

The results of the Box-Tidwell test for the continuous variables and per technology are presented in Appendix C. The linearity of the logit has been violated for at least one variable per technology. In models with large samples violation of this assumption is not critical (Hassan, 2020). Nonetheless, this leads to specification error (Menard, 2002). The implications of this violation are discussed along with the other limitations of this study in chapter 6.

4.3.2. Collinearity and multicollinearity

Correlation matrices and multicollinearity diagnostics are presented in Appendix D and E. A few general inferences can be made based on these matrices. The correlations above *.80* were observed for most technologies between ALLY and NON-LEADER (with the highest value of *.854* for high-speed rail). This high correlation can be explained by the fact among adopter countries there are a few leaders, thus NON-LEADER captures a lot of the prior adoptions. Nonetheless, there were no issues with multi-collinearity related to these variables. High positive correlations (but below *.80*) were also observed between control variables PATETNS, INVEST and HUMAN_CAP. This can be explained in a twofold manner. First, the countries with high GDP are usually the ones with high levels of human capital and the number of filed patents. The information embedded in these variables might be redundant. Second, both PATENTS and INVEST were log-transformed and as a result, have a similar distribution. These variables also exhibited higher VIF in multicollinearity diagnostics. Notably, the correlations between these three variables were lower using untransformed values. Furthermore, for all technologies, SIM exhibits VIF values above the threshold of *2.5* but below the threshold of *10*. This variable tends to increase with time as the number of adopters increases over time as well, thus the average distance between Polity scores tends to increase.

4.4. Model building and data analysis

The following paragraphs present model building steps and the regression results for each hypothesis.

4.5.1. Model building and selection

The models were built using the stepwise method. First, the univariable analysis with only the independent variable was carried out. Second, the control variables were added taking the purposeful approach. For consistency with the assumptions, the control variables were inserted in consequent models regardless of their statistical significance. For all models, the relevant variables were entered in a single step, the cut-off value was *0.5*.

The models were built as follows:

- Model 1: only with the independent variable.
- Model 2: with the independent variable and the control variables with good coverage.
  Included control variables: NEIGHBOR, STABILITY, REGIME, TIME_LAG.
- Model 3: with the independent variable and the control variables with average coverage.
  Included control variables: NEIGHBOR, STABILITY, REGIME, TIME_LAG, PATENTS, TRADE, INVEST, SURFACE.
- Model 4: with the independent variable and all control variables.
  Included control variables: NEIGHBOR, STABILITY, REGIME, TIME_LAG, PATENTS, TRADE, INVEST, SURFACE, GOV_SIZE, HUMAN_CAP.

The first model allows testing the hypothesis is isolation from external factors. The inclusion of the control variables in the subsequent models was driven by the availability of the data points. Thus, to cover the full range of observations, the second model includes only the complete and almost complete variables (N>7000). The analysis is based on the results from the second step as the data is the most robust and covers the whole observation period. The third model serves as a robustness check of the analysis (N>5000). The fourth model includes all the remaining variables. For transparency, this chapter contains the results of the second analysis. Complete regression tables are presented in Appendix F.

4.5.2. Regression results

4.5.2.1. Independent variables

For each model, the quality indicators have been assessed and model 2 had the best quality indicators. In addition, it included the highest number of cases. Based on these grounds it was selected as the final model. Furthermore, the inclusion of the additional control variables in models 3 and 4 had a small effect on the regression coefficients, the conclusions from model 2 were thus not challenged. The most relevant information about model 2 has been extracted from Appendix F and presented in Table 4-4 (page 55).

The following paragraph describes the main patterns observed in Table 4-4 with respect to the independent variables. The patterns in control variables are addressed later in this chapter. Each hypothesis is assessed separately. Nonetheless, the Hosmer-Lemeshow test is significant in all cases (except for H_3 for higher-speed rail), indicating a poor fit of the model with the data. Because this finding applies to all models, it is addressed in the discussion section.

Hypothesis 1

The first hypothesis posited that prior adoptions by a country's allies will have a positive effect on this country's adoption likelihood. For all technologies, except for solar power, this relationship has been confirmed as indicated by the positive and significant coefficients. Model 2 is a significant improvement compared to model 1 without control variables (see Appendix F for more details), as all χ^2 in the Omnibus test are highly significant. Notably, for the telecommunication and meteorological satellites the improvement is the highest, which reflects the international launches by the allied states of the Arab League and the states associated in NATO. The weakest improvement was observed for marine power, which is sensible given that the technology is in the pick-up phase with only a few adopters worldwide. The values of Nagelkerke R^2 are satisfactory, indicating that a fair share of the variance in the outcome is explained by the model. Similarly to χ^2, this statistic is the worst for marine power. These findings are conclusive enough to accept H_1, with exception of solar power. Notably, the findings of the model 2 are coherent with univariate analysis, providing additional confidence in the conclusion.

Table 4-4 Extract of the logistic regression results for model 2, all hypotheses, all technologies

	Nuclear power		Solar power		Wind power		Marine power		Higher-speed rail		High-speed rail		Telecommunication satellites		Meteorological satellites	
	β	e^{β}	β	e^{β}	β	e^{β}	β	e^{β}	β	e^{β}	β	e^{β}	β	e^{β}	β	e^{β}
Hypothesis 1																
ALLY	**.040° *****	**1.041**	**-.008**	**.992**	**.019° ****	**1.019**	**.278° *****	**1.321**	**.083° *****	**1.086**	**.095° *****	**1.100**	**.168° *****	**1.183**	**.063° *****	**1.065**
NEIGBOR	.658 ***	1.932	.490 ***	1.633	.431 ***	1.539	-.151	.859	1.027 ***	2.792	1.027 ***	2.793	1.016 ***	2.763	1.838 ***	6.287
STABILITY	.016 ***	1.016	.026 ***	1.026	.028 ***	1.028	.015 ***	1.015	.017 ***	1.018	-.003	.997	.034 ***	1.035	.039 ***	1.040
REGIME	.097 ***	1.102	.086 ***	1.090	.132 ***	1.141	.031 **	1.032	.162 ***	1.176	.287 ***	1.333	.028 ***	1.028	.097 ***	1.101
TIME_LAG	.002	1.002	.139 ***	1.149	.118 ***	1.126	.021 ***	1.021	.007	1.007	.018 **	1.018	.033 ***	1.034	.012 **	1.013
Omnibus χ^2/Sig.	2051.885/.000		1768.598/.000		2414.520/.000		148.129/.000		1492.343/.000		684.183/.000		4143.119/.000		2954.433/.000	
H-L χ^2/Sig.	77.050/.000		19.918/.011		18.885/.015		15.857/.044		24.172/.002		35.671/.000		30.555/.000		24.369/.002	
Nagelkere R^2	.404		.522		.581		.129		.517		.391		.688		.741	
Hypothesis 2																
DISSIMILARITY	**-.001°**	**.999**	**.001° *****	**1.001**	**.000**	**1.000**	**.006°**	**1.006**	**.003**	**1.003**	**.026 *****	**1.026**	**.003 *****	**1.003**	**-.008° *****	**.992**
NEIGBOR	.699 ***	2.013	.465 ***	1.592	.490 ***	1.632	.142	1.152	1.108 ***	3.027	1.093 ***	2.982	1.239 ***	3.452	2.030 ***	7.614
STABILITY	.017 ***	1.017	.024 ***	1.024	.029 ***	1.029	.015 ***	1.015	.018 ***	1.018	-.004 *	.996	.033 ***	1.034	.040 ***	1.041
REGIME	.091 ***	1.096	.126 ***	1.134	.128 ***	1.137	.058 ***	1.060	.208 ***	1.231	.509 ***	1.663	.035 ***	1.036	.016	1.016
TIME_LAG	.006 **	1.006	.097 ***	1.102	.130 ***	1.139	.024 **	1.024	.012 **	1.012	.002	1.002	.024 ***	1.024	.035 ***	1.036
Omnibus χ^2/Sig.	2039.006/.000		1783.371/.000		2323.734/.000		1333.520/.000		1472.723/.000		699.688/.000		3566.453/.000		2970.822/.000	
H-L χ^2/Sig.	79.347/.000		18.625/.017		26.114/.001		15.059/.058		17.395/.026		19.250/.014		44.599/.000		19.681/.012	
Nagelkere R^2	.402		.526		.589		.117		.511		.399		.615		.744	
Hypothesis 3																
LEADER	**.887° *****	**2.427**	**.555° *****	**1.741**	**.451° *****	**1.570**	**.864° ***	**2.373**	**.278°**	**1.321**	**.443**	**1.558**	**.678° *****	**1.969**	**-.639° *****	**.528**
NON-LEADER	**-.199 ****	**.820**	**-.647 *****	**.524**	**-.451 *****	**.636**	**1.450° *****	**4.263**	**.915° *****	**2.497**	**1.010° *****	**2.745**	**.708° *****	**2.030**	**1.007° *****	**2.737**
NEIGBOR	.674 ***	1.962	.500 ***	1.649	.453 ***	1.573	-.283	.753	.939 ***	2.557	.926 ***	2.525	1.199 ***	3.317	1.824 ***	6.196
STABILITY	.018 ***	1.018	.025 ***	1.026	.028 ***	1.029	.016 ***	1.016	.018 ***	1.018	-.002	.998	.035 ***	1.036	.038 ***	1.039
REGIME	.092 ***	1.096	.077 ***	1.080	.129 ***	1.137	.001	1.001	.152 ***	1.165	.270 ***	1.310	.003	1.003	.120 ***	1.127
TIME_LAG	.004	1.004	.147 ***	1.159	.126 ***	1.134	.026 ***	1.026	.018 ***	1.019	.020 ***	1.020	.043 ***	1.044	.010	1.010
Omnibus χ^2/Sig.	2127.429/.000		1803.044/.000		2430.729/.000		176.904/.000		1532.924/.000		709.855/.000		3727.793/.000		2967.036/.000	
H-L χ^2/Sig.	55.072/.000		23.538/.003		19.974/.010		28.401/.000		10.047/.262		27.859/.001		19.093/.014		20.588/.008	
Nagelkere R^2	.417		.530		.584		.154		.529		.405		.636		.743	

* $p \leq .10$, ** $p \leq .05$, *** $p \leq .01$

Notes:

- **Bold**: independent variables; normal text: control variables and model quality
- Green highlight: the direction and significance of the term confirm the hypothesis,
- Red highlight: the direction and/or significance of the term disprove the hypothesis,
- ° annotation: the direction and significance of the term is coherent between univariate analysis and the model (annotations only for the independent variables)

Hypothesis 2

The second hypothesized relationship was that the countries that are politically similar will adopt the same technologies. Low values of the variable DISSIMILARITY indicate a small political distance between adopter countries. Therefore, negatives signs of the coefficients would confirm the hypothesis. The H_2 holds true only for the meteorological satellites. For all other technologies, the coefficient has the wrong sign or is statistically insignificant. Furthermore, there was little coherence between the univariate model and the analyzed model. In conclusion, H_2 is rejected.

Hypothesis 3

Based on the theoretical framework it was postulated that the adoption by the leader among a country's allies will have a higher influence than by a non-leader. Constructing of LEADER and NON-LEADER variables as categorical allows to distill these effects through analysis of the odds ratios (e^{β}). The odds ratio represents the increase of odds of the outcome in case of the change of the category (here from 0 to 1). No pattern applicable to all technologies could be observed. Interpretation of the results by sector proved more useful to draw conclusions.

First, in the energy sector except for marine power, the odds ratios were higher for all technologies for the variable LEADER, and coherent with univariate analysis. However, the coefficients for NON-LEADER were negative and incoherent with model 1. This is surprising because it suggests that adoption by non-leading allies would decrease the odds of adoption, contradicting H_1. For marine power, the coefficient associated with LEADER was slightly insignificant and the odds ratio were higher for NON-LEADER.

Second, in the transport sector, the coefficients are insignificant for LEADER. Interestingly, the effects related to adoption by non-leaders (NON-LEADER) are positive and have higher odds ratios than LEADER. Interestingly, the strength of the respective influence of adoption by the leader and non-leaders is the opposite of what was posited in the hypothesis.

Third, the results for the space sector are similar to what was observed for the transport sector with the difference that the coefficients associated with LEADER are significant. The conclusions are coherent with the univariate analysis for both variables and both technologies. Remarkably, the influence of the adoption by non-leading allies was stronger than by the leader.

Across all technologies, the Omnibus test is significant, and the improvement of deviance is satisfactory. The values of Nagelkerke R^2 indicate that a high proportion of the variance is explained by the model. Nonetheless, as observed for H_1, marine power is a negative outlier. In conclusion, the data partially support H_3, it is valid for the energy sector technologies with exception of the marine power. Furthermore, the evidence of the transportation and space sectors disprove the hypothesis and suggests the opposite direction of the relationship.

4.5.2.2. Control variables

The coefficients of the control variables were in general in line with the expectations. The following paragraphs briefly comment on the coefficients of the control variables.

First, the neighbor effect (NEIGHBOR) was significant and had a relatively strong influence; the reported odds ratios were consistently high. This is in line with the literature on geographical spillovers (Jaffe et al., 1993). The only outlier is the marine power where the neighbor effect was statistically insignificant, despite the exclusion of landlocked countries in the analysis of this technology. For that reason, this pattern came as a surprise. Nonetheless, the geographical conditions highly constrain the areas where these technologies are feasible. The potential for harvesting marine power highly depends on the strengths of the currents and waves and cannot be merely based on access to the sea (Weiss et al., 2018). The country exclusion logic could be improved by incorporating a rule based on natural resource availability.

Second, the results show that political stability (STABILTY) had a positive effect on technology adoption for all technologies except for high-speed rail. This confirms the notion that more stable political systems have longer time horizons and are better suited to make complex decisions regarding large-scale infrastructure technologies.

Third, the coefficients of (REGIME) variable were mostly positive and significant. This implies that the more democratic the state, the more likely it is to adopt one of the infrastructural technologies. The direction of the influence of the regime was hypothesized mostly on earlier studies of consumer technology. This research shows that this relationship holds water also for large-scale infrastructural technologies.

Fourth, the more time passed since the first adoption the more likely it was for a given country to become a technology adopter (TIME_LAG). This can be associated with the fact that the knowledge about technologies could disseminate throughout the international networks and states were able to exchange information about them and eventually decide to use them. Notably, time turned out to be insignificant for the first and the third hypothesis in the case of nuclear power. Thus, the model was able to capture dying out the diffusion of nuclear power.

4.5.2.3. Extended analysis of the unselected models

Lastly, the most relevant findings of the unselected models are discussed to put the results in a broader context and fully exploit the analytical model.

Models 3 and 4 include approximately 60% and 15% of the cases from the sample. Thus, any inferences should be made with precautions. It must be noted that there was a high degree of agreement between models 2 and 3 when it comes to independent variables. However, significance tended to be lower because of the smaller sample size leading to lower statistical power. The inter-model reliability was the worst for model 4. The discarded models performed better at Hosmer-Lemeshow test. However, this is related to the decreasing reliability of the Hosmer-Lemeshow test as the sample size increases (Hosmer et al., 1997; Nattino et al., 2020).

For model 3, when it comes to the control variables the observed coefficients were in line with the expectations for PATENTS and SURFACE, both with a positive influence on the adoption odds ratio. However, there were five noteworthy phenomena related to other control variables.

First, the increasing trade openness (TRADE) was found to decrease the odds ratio of adoption in the majority of the regressions in model 3 and increase in model 4. Some light could be shed on this observation when considering the effects of the interaction of trade liberalization and democratization on technology adoption (Cervellati et al., 2018). The researchers have found that trade openness alone can have a negative influence on technology adoption, and positive when the interaction with the political regime is considered. Superposing this with the fact that the samples in models 3 and 4 are not representative of the whole population, with average polity scores of *1.82* and *6.78*, the change of the TRADE coefficient to negative for the more democratic sample becomes sensible. Nonetheless, to confirm this explanation, interaction effects between variables would have to be included in the model.

Second, unstable signs of coefficients between models 3 and 4 were observed for PATENTS, HUMAN_CAP, and INVEST. Contrary to expectations, in many cases the coefficients were negative. Human capital and the number of patents is generally high in developed countries. Including all three in one model is problematic because they measure very similar characteristics of a country. Furthermore, these variables have the highest multicollinearity indicators suggesting overfitting and the Nagelekere R^2 is higher for most regressions for the model without human capital variable. The modeling could be improved either by the elimination of one of the redundant variables or by including interactions between them (Midi et al., 2010).

Third, the doubling of the country's GDP per capita (variable INVEST) exhibited unstable, and oftentimes insignificant, coefficients between the models. Literature research did not yield any useful hints to explain this. As a robustness check, the analysis was executed using non-transformed GPD per capita values and the coefficients were positive, as expected based on the literature review. This unexpected variable behavior shows that variable transformation is not always the best methodological choice (Field, 2013). Alternatively, the variable could be formulated differently by controlling for the nominal country's GDP that better reflects a country's economy size than GDP per capita that shows the relative economic wealth of countries.

Fourth, the influence of large governments (GOV_SIZE) was negative for all technologies, except for higher-speed rail. This is consistent with the literature on consumer goods, as stipulated in the methodology section. However, because the government size was operationalized as the share of central spending in a country's GDP and because the studied technologies are infrastructural, the opposite effect was expected. In the case of infrastructure, when the investments are typically financed at the central level, the adopters were expected to have large governments. However, these unexpected findings suggest that oversized governments are detrimental when it comes to investment in infrastructural technologies. Additional investigation of the mechanisms and optimal government size for infrastructural technology adoption represent an appealing avenue for further research.

Lastly, there was one unstable model (model 4, marine power, H_3). When all control variables were entered SPSS was unable to find a convergent solution. The estimated coefficient for NON-LEADER was extremely large. Hosmer (2013) suggests three potential root causes: "thin" data (not enough outcomes and small frequencies of categorical covariates), complete separation, or multicollinearity. Multicollinearity was ruled out because none of the variables achieved alerting VIF values. "Thin" data is a likely explanation because marine power variables ADOPTION, LEADER and NON-LEADER had the lowest frequencies of value 1 in the whole sample. However, the frequencies of these variables low for high-speed rail were and the model converged after 9 iterations. This would speak for the complete separation rationale, or a mixed effect of "thin" data and complete separation, especially because the model converged when GOV_SIZE was excluded. Yet, an in-depth investigation was omitted as the model 4 not selected to draw conclusions.

5. Conclusion

The purpose of this research was to scrutinize to what extent alliances between countries affect infrastructural technology adoption decisions by national governments. Based on the conceptual framework derived from the diffusion of innovations paradigm, social contagion theory and the realist school of thought in IR, three hypotheses were posited. They were tested using logistic regression to analyze worldwide data. The dataset was built using secondary sources, collecting data for 161 countries in the period between 1954 and 2012 for eight technologies that have the potential to contribute to sustainability transitions: nuclear, solar, wind and marine power, higher- and high-speed rail, telecommunication, and meteorological satellites.

The analysis showed that prior adoption by the country's allies had a positive influence on adoption likelihood by that country. The more allies of the country were adopters the more likely it was for that country to also become an adopter. The influence of adoption by the leader and non-leader of a country's alliance network had mixed effects and depended on the technological sector. This suggests that the diffusion does not happen in a hierarchical manner but that the sources of influence are distributed among alliance members. The hypothesis about the similarity of political systems was rejected. The countries with similar political institutions did not mimic each other in regard to the choice of technologies they used. All three hypotheses considered, the alliances had a positive influence on technology adoption by national governments and that the structure and the interactions within the international state system played an important role in technology diffusion. Social contagion at least partially explained cross-country adoption patterns, but further study is necessary to better substantiate these mechanisms. The varying results across technologies and technological sectors indicate that the characteristics of the technology itself have an impact on the diffusion rates. The suggestions for further research are presented in the final chapter.

The study contributed to the fields of international relations, innovation sciences and sustainability. It added to the literature on technology adoption determinants and gave insights into the political factors at a global level. It also paved the way for meta-studies with large samples of countries and technologies. Furthermore, the interdisciplinary approach allowed to bridge between the fields of innovation, behavioral and political sciences and proved the usefulness of cross-disciplinary research. Including multiple clean technologies contributed to the field of sustainability by shedding light on the mechanisms enabling global diffusion of these technologies.

To conclude, the findings of the study can be used by national governments in shaping their domestic and foreign policy. Engaging in relationships with other states has advantages for governments interested in exporting their infrastructural technologies but also for governments of countries that intend to pursue sustainability goals through the adoption of infrastructural technology from abroad. These implications are discussed in detail in the following chapter.

6. Discussion

This chapter acknowledges the limitations of this thesis, discusses the implications of the findings and suggests avenues for further research.

6.1. Limitations and areas for improvement

Theoretical limitations

Only a part of the international relations was captured because the relationships between states have been operationalized through military alliances. Apart from military alliances, countries can have other types of international relations: diplomatic ties or economic cooperation programs. The choice of alliances lens has introduced a limitation in that the adoption by neutral states could not be explained through the contagion process. For instance, three outliers can be mentioned to exemplify that: Austria, Sweden, and Switzerland. Each country has been neutral at least since the end of World War II or longer, and each of these countries is an adopter of at least a few technologies from the sample. Despite this limitation, contagion still could a significant part of the big picture of the diffusion process. For example, after the collapse of the Soviet Union, several former allies remained adopters of nuclear power plants while the model indicated otherwise (positive outliers). To address this drawback, this research could be extended to analysis of other types of relationships between states to provide more robustness of the results. Furthermore, the strength of the relationships could be incorporated as an additional measurement dimension. For instance, counting how many other treaties have been co-signed by country pairs would allow quantifying the level of connectedness.

The shortcoming of the realist approach to IR is the most evident in explaining the adoption of space technologies. Because of the focus on state actors, the role of other international organizations was neglected. For instance, the states associated with the Arab League had a joint space program for telecommunication satellites. In this case, there was a perfect overlap between the allied states and the adopters of technology. However, most NATO countries have likewise cooperatively sent satellites to space but the joint launches happened through European Space Agency (ESA) projects and not through cooperation within NATO structures. At the same time, there is a significant level of overlap between member states of NATO and ESA, especially for most of the West-European countries. On the other hand, it can be argued that the decision of a country to join either of the organizations has a strategic political nature and is driven by its national interest. Unfortunately, these “background” mechanisms remain uncaptured in the current conceptual framework. Explaining the causal mechanism of the significant overlap between NATO and ESA was beyond the scope of this study an interesting but represents an interesting case for further inquiry.

Data

The use of secondary data offered the advantage of carrying out the analysis of a big amount of data in a short time. Nonetheless, certain limitations of secondary data must be acknowledged. Despite triangulation and reliance on trustworthy sources, it was impossible to distill only infrastructural scale data for solar and wind power. The data for these two technologies of electricity generation included also non-utility scale installation. In consequence, the classification of countries as adopters was less reliable than, for instance, for nuclear power, where data on every nuclear power plant available. Nonetheless, this shortcoming can be defended by the fact that even for adoption by individuals some sort of legal permit is typically required to build a windmill, for instance. Thus, even if the governments did not actively adopt the technologies, they must have indirectly enabled adoption by individuals by adjusting the law to regulate the use of specific technology. On the other hand, similarly to nuclear power, rail and space technologies could be traced down to major projects. Given that more time had been allocated for data collection, the weakest sources could have been replaced with primary data collection, for example by surveying the respective government agencies about utility-scale wind and solar parks.

Model quality

Violation of the linearity of the logit assumption leads to specification error. In consequence, the coefficients might be systematically biased: either over- or underestimated (Menard, 2002). The computed probabilities should be thus taken with a grain of salt, especially for the outlier cases with estimated probabilities around the cut-off value. Menard (2002) suggests a few remedies such as further investigation of the non-linearity and transformation of the problematic variables. Nonetheless, the purpose of this study was to identify the significant factors and determine the signs of the coefficients. Thus, this limitation must be pointed out but does not have a critical impact on the validity of the conclusions. Using a generalized additive model (GAM) instead of the generalized linear model (GLM) could be a remedy against the encountered non-linearities. GAMs are suitable when dealing with real-world data its social and political complexities (Beck & Jackman, 1998). The hypotheses could be re-assessed using a GAM framework in a follow-up research.

Furthermore, the significant results of the Hosmer-Lemeshow test signal the deficient accuracy of the estimated probabilities of the outcome. It must be noted that Hosmer-Lemeshow test has been criticized for yielding unreliable results when used with large sample sizes (Nattino et al., 2020), and when the values of the covariates differ widely (Hosmer et al., 1997). Thus, the poor performance of the model in Hosmer-Lemeshow test can be justified with its methodological shortcomings, given that the sample of this study falls into the beforementioned cases. The researchers have proposed several alternatives to the Hosmer-Lemeshow tests which could be implemented in the next iteration of model building (Hosmer et al., 1997). Nonetheless, this shortcoming is not critical as long as the model developed for this study in not used for making predictive claims about future adoption decision by countries.

Operationalization

The second hypothesis was rejected. However, a peculiar model behavior was observed. The coefficients associated with the term (DISSIMILARITY) were very close to zero and the odds ratios crossed 1 in half of the cases, yielding the coefficients insignificant. The variable was constructed as a sum of the absolute differences of polity scores between a county and all adopters at the time. For that reason, its value tended to increase with every new adopter country. Notably, the analysis of the Polity V dataset suggests convergence of the countries towards more democratic systems. The average polity score was *0.32* in 1954 and *4.08* in 2012, with standard deviations of *7.54* and *6.12*, respectively. On the other hand, there were countries on the opposite side of the polity spectrum that have adopted the same technologies around the same time. This would suggest that the (dis)similarity of the political systems in not a robust determinant of technology adoption. For instance, the USSR and the USA adopted nuclear power around the 1960s, or South Korea and China adopted high-speed rail around the 2000s. Unquestionably, no conclusions can be drawn from these observations. To gain more insight, the variable should enter in the analysis in a modified version before making any definitive statement.

Model building

The model building strategy, as proposed by Hosmer (2013), includes a step with the examination of the interactions of the variables. This step was skipped in the model building because only one independent variable was used for H_1 and H_2; and H_3 could be tested using two variables because the relative effects of leader and non-leader adoption were tested. Thus, considering practical considerations H_3 the interaction between LEADER and NON-LEADER was not examined. On the other hand, extended analysis of interactions would be sensible for some of the control variables but was beyond the scope of this study.

6.2. Theoretical and practical implications

To sum up, previous studies investigated the determinants of technology adoption looking at either technology specific or country specific factors, oftentimes using the case study of a single technology or a country. This study took a political perspective using a cross-country approach with a sample of eight infrastructural technologies. The conceptual framework drawing from social contagion and Roger's model of diffusion of innovations was applied to the field of IR and was used to examine how relationships between countries affect infrastructural technology diffusion.

From the theoretical point of view, the results showed that the adoption by a country's allies increased the odds of adoption by the country, supporting the first hypothesis. This finding did not apply to only one technology: solar power. It must be noted that solar power was the only widespread technology that diffused to almost the entire population, at the end of the observation period 117 out of 152 countries in the sample have adopted it. The right-hand side of the S-curve in Figure 4-1 was horizontal. This exception is difficult to explain with the conceptual framework developed in this study. Nonetheless, some insights can be provided when looking at technology-related factors. First, it must be noted that solar power technology is relatively easy to adopt. Solar electricity can be produced not only in utility-scale solar parks but also by induvial users in decentralized installations (i.e., household rooftop). Second, among all technologies, solar power is relatively the least politically sensitive. By contrast, the use of nuclear power technology can be of political concern because of the possibility of "misuse" of nuclear material for military purposes. Similarly, access to space technologies can be crucial from the point of view of national interest and national security (Moon Cronk, 2021).

Contrary to expectations, data showed that the political similarity was insignificant or that it had a negative influence on technology adoption. The second hypothesis was disproved. This suggests that diffusion through emulation does not apply to the diffusion of infrastructural technology. However, there were some methodological issues with this variable, which were addressed in the previous section. On the other hand, the second hypothesis was drawn upon the diffusion of innovations paradigm. Disproval of the second hypothesis confirms that Roger's paradigm is useful for describing the diffusion but is of limited utility to opening up of the "black box" behind it. The disproval of this hypothesis indicates that the diffusion mechanism is driven by the interactions between the agents, as stipulated by the social contagion theory. Even if two countries are similar with respect to their political systems, the contagion will not occur unless the states interact with each other.

With respect to the influence of the leader, no single conclusion applicable to all technologies could be drawn. At the same time, three distinctive patterns were observed for each technological sector. For all energy technologies, except for marine power, adoption by the leader had a stronger influence on the odds ratio than adoption by a non-leading country in the alliance, in line with the third hypothesis. Marine power is another exception in this sector for three reasons. First, it the least spread technology, used by only 16 countries. Second, it has not been adopted by any of the most frequently observed alliance leaders. Third, the technology can be potentially adopted only by countries with access to the sea with harvestable current and wave resources. Thus, it seems that in the case of marine power the technology-related characteristics override the contagion mechanism. For transportation and space technologies adoption by non-leader had a strong positive influence on the odds ratio. These varying patterns across technologies have three theoretical implications.

First, these patterns should be examined against the background of neighbor effects. In all regressions, the odds ratios associated with the neighbor effect were relatively high. This is sensible as oftentimes countries from alliances with their neighbors and suggests that network effects are at play (as shown by correlation coefficients between NON-LEADER and NEIGHBOR, ranging between *.368* and *.493*; see Appendix E). Notably, the neighbor effect was strong in the case of transportation technologies and space technologies. In the first sector, this can be associated with the positive adoption externalities between adjacent countries. In the latter, oftentimes the satellites were jointly launched by multiple countries that were neighbors and were members of the same alliance. They had incentives to do so to share the costs of the space program but also, they could share satellites to provide telecommunication or meteorological services. Furthermore, it can be argued that the varying effects of adoption by the leader are in line with the original theory of Ryan and Gross (1943). Their study showed that political leadership differed from technological leadership. Analysis of the alliance networks represents an appealing avenue for further research to identify the most influential non-leader actors in the alliances.

Second, it suggests that the characteristics of the innovation play a significant role in adoption decisions. Contagion occurs through "contact" between countries and is affected by the potency of the influence source but also it also seems to depend on the "contagiousness" of the technology itself. A similar observation has been made by Geroski (2000) in a micro-level study of the epidemic diffusion model: simpler and easier to use technologies spread faster than more complex ones. Potential technology-related explanations were proposed in this discussion chapter. However, due to a lack of analytical framework, these differences could not be assessed in a systematic manner. Further research is needed to develop an analytical frame for studying the impact of infrastructural technology characteristics on technology diffusion in the international context. Moreover, further research should be extended to other technological sectors to demarcate the patterns across a larger sample of technologies.

In brief, as an alliance fills up with adopters the likelihood of adoption by another country of that alliance increases. However, the contagion process does not extend to all technologies. The exceptions suggest that, contrarily to the original theory, the technology characteristics can play a role when it comes to the adoption of infrastructural technologies within the international state system. Furthermore, the mixed effects of the influence of leaders and non-leaders suggest that a country with the most power is not always the most potent source of influence, and that neighbor effect plays a role in the diffusion process. This implies that the diffusion is not hierarchical and does not have to start from the leader.

Moving on to the practical implications, the findings of this study are interesting in the context of technology diplomacy literature. Many countries have innovation attachés in their diplomacy offices (Leijten, 2017). Innovation diplomacy is part of a country's foreign policy. It involves the facilitation of innovation and adoption of innovations, and focuses on building national gains in science, technology, and innovation through diplomatic means (Griset, 2020; Leijten, 2017). Leijten (2017) argues that the innovation attachés can support the competitiveness of their nations by signaling collaboration opportunities of directly influencing policies of the host countries. Thus, in relation to the conceptual framework of this study, the diplomats can be seen as the change agents who actively pursue to influence adoption decisions. The example of Japan shows that alignment of domestic and foreign policies allows to reinforce political and economic interests and promote local technologies abroad (Okano-Heijmans, 2012). In other words, diplomatic relationships offer means for the creation of contagion channels for international technology diffusion. This has two practical implications. First, strengthening and expansion of the relationships with other states offer means of commercialization of the “green” technologies for producer countries, while increasing soft power (Yakushiji, 2009). This practice has been widely applied by China (Jakobson, 2009). Second, for countries that are not at the technological frontier, participation in international treaties offers an opportunity to pursue domestic and global sustainability goals through the adoption of technology from abroad.

To conclude, the conceptual framework built on the theory of social contagion proved to be useful in studying the influence of international relations on technology adoption. Indeed, interactions between nation-states have a positive influence on diffusion. The findings show that adoption by the leader does not always have a stronger influence on the country’s propensity to adopt compared to adoption by another of the country’s allies. This suggests that the leadership is distributed across different states within one network. Practically, it means that countries can and should use their foreign policy tools when they are interested in exporting their infrastructural technologies abroad but also when they want to gain access to the technologies that they cannot develop themselves. Lastly, the varying results across technological sectors suggest that the diffusion depends on “contagiousness” of technologies. More research is needed to follow up on the results and further the understanding of the adoption determinants. Future research can provide a deeper understanding of social contagion among countries through examination of the networks. Because different patterns were observed across the technological sectors, even larger samples of technologies can be analyzed to grasp the technology-related factors that impact diffusion through cross-country contagion. Including technology-specific factors offers a promise of more in-depth insights into this phenomenon.

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Appendix A. County names, codes, timespans, and exclusion notes

Note: only sovereign states were included in the list. Dash in the columns "Begin" and "End" denotes that the country existed before and/or after the timeframe of the observation period (the dates have been adapted from the Polity V dataset).

Table A-1 Overview of the countries

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Afghanistan	AFG	-	-				Yes
Albania	ALB	-	-				
Algeria	ALG	1962	-				
Andorra	AND	-	-	Yes	No Polity data, no data on alliances		Yes
Angola	ANG	1975	-				
Antigua and Barbuda	AAB	-	-	Yes	No Polity data		
Argentina	ARG	-	-				
Armenia	ARM	1991	-				Yes
Australia	AUL	-	-				
Austria	AUS	-	-			Since 1955	Yes
Azerbaijan	AZE	1991	-				Yes
Bahamas	BHM	-	-	Yes	No Polity data		
Bahrain	BAH	1971	-				
Bangladesh	BNG	1972	-				
Barbados	BAR	-	-	Yes	No Polity data		
Belarus	BLR	1991	-				Yes
Belgium	BEL	-	-				
Belize	BLZ	-	-	Yes	No Polity data		
Benin	BEN	1960	-				
Bhutan	BHU	-	-	Yes	No data on alliances		Yes

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Bolivia	BOL	-	-				Yes
Bosnia and Herzegovina	BOS	1992	-				
Botswana	BOT	-	-	Yes	No data on alliances		Yes
Brazil	BRA	-	-				
Brunei	BRU	-	-	Yes	No Polity data, no data on alliances		
Bulgaria	BUL	-	-				
Burkina Faso	BFO	1960	-				Yes
Burundi	BUI	1962	-				Yes
Cambodia	CAM	-	-			Since 1955 to 1970	
Cameroon	CAO	1960	-				
Canada	CAN	-	-				
Cape Verde / Cabo Verde	CAP	1975	-				
Central African Republic	CEN	1960	-				Yes
Chad	CHA	1960	-				Yes
Chile	CHL	-	-				
China	CHN	-	-				
Colombia	COL	-	-				
Comoros	COM	1975	-	Yes	No data on alliances		
Congo / Congo-Brazzaville	CON	1960	-				
Costa Rica	COS	-	-			Since 1949; nonetheless member of the Rio Treaty	
Croatia	CRO	1991	-				
Cuba	CUB	-	-				
Cyprus	CYP	1960	-				
Czech Republic / Czechia	CZR	1993	-				Yes
Czechoslovakia	CZE	-	1992				Yes
Democratic Republic of the Congo / Congo-Kinshasa	DRC	1960	-				

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Denmark	DEN	-	-				
Djibouti	DJI	1977	-				
Dominica	DMA	-	-	Yes	No Polity data		
Dominican Republic	DOM	-	-				
East Timor / Timor-Leste	ETM	2002	-	Yes	No data on alliances		
Ecuador	ECU	-	-				
Egypt	EGY	-	-				
El Salvador	SAL	-	-				
Equatorial Guinea	EQG	1968	-				
Eritrea	ERI	1993	-				
Estonia	EST	-	-				
Ethiopia	ETH	-	-				Yes
Fiji	FIJ	1970	-	Yes	No data on alliances		
Finland	FIN	-	-			Since 1955	
France	FRN	-	-				
Gabon	GAB	1960	-				
Gambia	GAM	1965	-				
Georgia	GRG	1991	-				
German Democratic Republic / East Germany	GDR	-	1989				
German Federal Republic / West Germany	GFR	-	1989				
Germany	GMY	1990	-				
Ghana	GHA	1960	-			Since 2012	
Greece	GRC	-	-				
Grenada	GRN	-	-	Yes	No Polity data		
Guatemala	GUA	-	-				
Guinea	GUI	1958	-				

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Guinea-Bissau	GNB	-	-				
Guyana	GUY	-	-				
Haiti	HAI	-	-				
Honduras	HON	-	-				
Hungary	HUN	-	-				Yes
Iceland	ICE	-	-	Yes	No Polity data		
India	IND	-	-				
Indonesia	INS	-	-				
Iran	IRN	-	-				
Iraq	IRQ	-	-				
Ireland	IRE	-	-			Since 1939	
Israel	ISR	-	-				
Italy	ITA	-	-				
Ivory Coast / Côte d'Ivoire	CDI	1960	-				
Jamaica	JAM	1959	-				
Japan	JPN	-	-			Since 1947, nonetheless remains in an alliance with the USA	
Jordan	JOR	-	-				
Kazakhstan	KZK	1991	-				Yes
Kenya	KEN	1963	-				
Kiribati	KIR	-	-	Yes	No Polity data, no data on alliances		
Kosovo	KOS	2008	-	Yes	No data on alliances		Yes
Kuwait	KUW	1963	-				
Kyrgyzstan	KYR	1991	-				Yes
Laos	LAO	1954	-	Yes	No data on alliances	Since 1955 to 1970	Yes
Latvia	LAT	-	-				
Lebanon	LEB	-	-				
Lesotho	LES	-	-	Yes	No data on alliances		Yes

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Liberia	LBR	-	-				
Libya	LIB	-	-				
Liechtenstein	LIE	-	-	Yes	No Polity data, no data on alliances	Since 1868	Yes
Lithuania	LIT	-	-				
Luxembourg	LUX	-	-				Yes
Macedonia / North Macedonia	MAC	1991	-	Yes	No data on alliances		Yes
Madagascar	MAG	1961	-				
Malawi	MAW	1964	-	Yes	No data on alliances		Yes
Malaysia	MAL	1957	-				
Maldives	MAD	1965	-	Yes	No Polity data		
Mali	MLI	1960	-				Yes
Malta	MLT	1964	-	Yes	No Polity data, no data on alliances		
Marshall Islands	MSI	-	-	Yes	No Polity data		
Mauritania	MAA	1960	-				
Mauritius	MAS	1968	-				
Mexico	MEX	-	-			Since 1930, nonetheless member of the Rio Treaty	
Micronesia	FSM	-	-	Yes	No Polity data		
Moldova	MLD	1991	-				Yes
Monaco	MNC	-	-	Yes	No Polity data		
Mongolia	MON	-	-				Yes
Montenegro	MNG	2006	-	Yes	No data on alliances		
Morocco	MOR	-	-				
Mozambique	MZM	1975	-				
Myanmar / Burma	MYA	-	-				
Namibia	NAM	-	-				
Nauru	NAU	1968	-	Yes	No Polity data, no data on alliances		
Nepal	NEP	-	-	Yes	No data on alliances		Yes

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Netherlands	NTH	-	-				
New Zealand	NEW	-	-				
Nicaragua	NIC	-	-				
Niger	NIR	1960	-				Yes
Nigeria	NIG	1960	-				
People's Republic of Korea / North Korea	PRK	-	-				
Norway	NOR	-	-				
Oman	OMA	-	-				
Pakistan	PAK	1972	-				
Palau	PAL	-	-	Yes	No Polity data, no data on alliances		
Panama	PAN	-	-			Since 1989, nonetheless member of the Rio Treaty	
Papua New Guinea	PNG	1975	-	Yes	No data on alliances		
Paraguay	PAR	-	-				Yes
Peru	PER	-	-				
Philippines	PHI	-	-				
Poland	POL	-	-				
Portugal	POR	-	-				
Qatar	QAT	1971	-				
Republic of Vietnam / South Vietnam	RVN	1955	1975	Yes	No Polity data		
Romania	ROM	-	-				
Russia / Russian Federation	RUS	1991	-				
Rwanda	RWA	1961	-				Yes
Samoa	WSM	1962	-	Yes	No Polity data, no data on alliances		
San Marino	SNM	-	-	Yes	No Polity data, no data on alliances		Yes
Sao Tome and Principe	STP	1975	-	Yes	No Polity data		

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Saudi Arabia	SAU	-	-				
Senegal	SEN	1960	-				
Serbia	SBA	2006	-			Since 2007	Yes
Serbia and Montenegro	SBM	1992	2005				
Seychelles	SEY	-	-	Yes	No Polity data, no data on alliances		
Sierra Leone	SIE	1961	-				
Singapore	SIN	1959	-			Since 1965	
Slovakia	SLO	1993	-				
Slovenia	SLV	1991	-				
Solomon Islands	SOL	-	-	Yes	No data on alliances		
Somalia	SOM	1960	-				
South Africa	SAF	-	-				
Republic of Korea / South Korea	ROK	-	-				
South Sudan	SSD	2011	-				Yes
Spain	SPN	-	-				
Sri Lanka	SRI	-	-	Yes	No data on alliances		
St. Kitts and Nevis	SKN	-	-	Yes	No Polity data		
St. Lucia	SLU	-	-	Yes	No Polity data		
St. Vincent and the Grenadines	SVG	-	-	Yes	No Polity data		
Sudan / North Sudan	SUD	1954	-				
Suriname	SUR	1975	-				
Swaziland / Eswatini	SWA	1968	-				Yes
Sweden	SWD	-	-			Since 1812	
Switzerland	SWZ	-	-			Since 1815	Yes
Syria	SYR	-	-				
Taiwan	TAW	-	-				
Tajikistan	TAJ	1991	-				Yes
Tanzania	TAZ	1961	-				

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Thailand	THI	-	-				
Togo	TOG	1961	-				
Tonga	TON	1970	-	Yes	No Polity data, no data on alliances		
Trinidad and Tobago	TRI	1962	-				
Tunisia	TUN	1959	-				
Turkey	TUR	-	-				
Turkmenistan	TKM	1991	-			Since 1995, nonetheless member of the Collective Security Treaty Organization	Yes
Tuvalu	TUV	-	-	Yes	No Polity data, no data on alliances		
Uganda	UGA	1962	-				Yes
Ukraine	UKR	1991	-			Since 1991 to 2014, nonetheless entered alliances with other countries	
Union of Soviet Socialist Republics	USS	-	1990				
United Arab Emirates	UAE	1971	-				
United Kingdom	UKG	-	-				
United States of America	USA	-	-				
Uruguay	URU	-	-				
Uzbekistan	UZB	1991	-			Since 2012	Yes
Vanuatu	VAN	-	-	Yes	No Polity data, no data on alliances		
Venezuela	VEN	-	-				
Vietnam	DRV	1954	-				
Yemen	YEM	1990	-				
Yemen Arab Republic	YAR	-	1989		Lack of data on adoption for solar, wind and marine power		
Yemen People's Republic	YPR	1967	1989		Lack of data on adoption for solar, wind and marine power		
Yugoslavia	YUG	-	1991			Since 1949 to 1991	

Country name	Code	Begin	End	Exclusion	Reason for exclusion	Neutrality: dates and comments	Landlocked
Zambia	ZAM	1964	-				Yes
Zanzibar	ZAN	1963	1964	Yes	No Polity data		
Zimbabwe	ZIM	1970	-				Yes

Appendix B. List of the major multilateral alliances

The alliances have been identified using the COW data set (Gibler, 2020). Unless otherwise specified (in parentheses), all countires were members for the whole duration of the alliance. For brevity, the list contains only the major multilateral alliances.

Table B-1 Main alliances

Alliance name	Begin	End	Type	Member states
Southeast Asia Collective Defense Treaty	1954	1973	Entente	United States, United Kingdom, France, Pakistan, Thailand, Philippines, Australia, and New Zealand.
Pact of Mutual Cooperation between Iraq and Turkey (Baghdad Pact)	1955	1978	Entente	Turkey, Iraq, United Kingdom (April 5, 1955); Pakistan (September 23, 1955); Iran (November 3, 1955); and the United States (July 28, 1958).
League of Arab States (Arab League)	1945	-	Entente	Egypt, Iraq, Jordan, Lebanon, Saudi Arabia, Syria, Yemen (May 5, 1945); Libya (March 28, 1953); Sudan (January 19, 1956);Morocco and Tunisia (October 1, 1958); Kuwait (July 20, 1961); Algeria (August 16, 1962); the United Arab Emirates, (June 12, 1972); Bahrain and Qatar (September 11, 1971); Oman (September 29, 1971);Mauritania (November 26, 1973); Somalia (February 14, 1974); Palestine (September 9, 1976); Djibouti (April 9, 1977); Comoros (November 20, 1993); Eritrea (observer since 2003); Venezuela (observer since 2006); India (observer since 2007).
North Atlantic Treaty (NATO)	1949	-	Defense	Original members included the United States, Canada, the United Kingdom, the Netherlands, Belgium, Luxembourg, France, Portugal, Italy, Norway, Denmark, and Iceland. The alliance expanded with the membership of Greece and Turkey (October 21, 1951); the German Federal Republic (October 23, 1954); Spain (December 10, 1981); the Czech Republic, Hungary, and Poland (December 16, 1997); and Bulgaria, Estonia, Latvia, Lithuania, Romania, Slovakia, and Slovenia (March 29, 2004). Germany replaced the membership of the German Federal Republic on October 3, 1990.
Warsaw Pact	1955	1991	Defense	Albania, Bulgaria, Czechoslovakia, German Democratic Republic, Hungary, Poland, Romania, and the Union of Soviet Socialist Republics
Treaty on Collective Security	1992	-	Defense	Armenia, Azerbaijan, Kazakhstan, Kyrgyz Republic, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan (September 24, 1993), Georgia (December 9, 1993), and Belarus (December 31, 1993).
Inter-American Treaty of Reciprocal Assistance (Rio Treaty)	1947	-	Defense	United States, Argentina, Haiti, Bolivia, Honduras, Brazil,Mexico, Chile, Colombia, Panama, Costa Rica, Paraguay, Dominican Republic, Uruguay,Venezuela, El Salvador, Guatemala, Cuba (until January 22, 1962), Nicaragua (entered October 15, 1948), Ecuador (entered November 10, 1949), Trinidad and Tobago (entered April 6, 1967), and Bahamas (entered November 8, 1982).

Table B-1 Main alliances

Alliance name	Begin	End	Type	Member states
Nairobi Pact	2006	-	Defense	Democratic Republic of the Congo, Angola, Burundi, Central African Republic, Republic of Congo, Kenya, Rwanda, Sudan, Tanzania, Uganda and Zambia.
Non-Aggression and Defense Assistance Agreement between the States of the West African Economic Community (CEAO) and Togo	1978	-	Defense	Burkina Faso, Côte d'Ivoire,Mali, Mauritania, Niger, Senegal, and Togo; Benin, Cape Verde, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Nigeria, and Sierra Leone joined on April 22, 1978.
Mutual Assistance Treaty between the countries of Economic Community of Central African States	2000	-	Defense	Cameroon, Gabon, Central African Republic, Chad, Congo, Democratic Republic of the Congo, Burundi, Rwanda, Angola, Equatorial Guinea, and Sao Tome and Principe.

Appendix C. Linearity of the logit

Table C-1 Linearity of the logit

	Nuclear power	Solar power	Wind power	Marine power	Higher-speed rail	High-speed rail	Telecommunication satellites	Meteorological satellites
ln(ALLY)×ALLY	.253	.159	.164	.028	.071	.000*	.000*	.024
ln(DISSIMILARITY)×DISSIMILARITY	.461	.015	.000*	.883	.495	.049	.028	.213
ln(NEIGHBOR)×NEIGHBOR	.000*	.002*	.000*	.538	.046*	.084	.063	.016*
ln(STABILITY)×STABILITY	.000*	.270	.024	.004*	.697	.691	.193	.235
ln(REGIME)×REGIME	.545	.678	.066	.440	.013	.027	.801	.115
ln(TIME_LAG)×TIME_LAG	.278	.529	.001*	.001*	.825	.071	.000*	.000*
ln(PATENTS)×PATENTS	.502	.156	.255	.000*	.566	.000*	.140	.005*
ln(TRADE)×TRADE	.000*	.029	.029	.009	.000*	.000*	.026	.151
ln(INVEST)×INVEST	.001*	.003*	.009	.395	.210	.037	.009	.001*
ln(SURFACE)×SURFACE	.001*	.000*	.000*	.272	.000*	.001	.224	.002*
ln(GOV_SIZE)×GOVS_SIZE	.006	.001*	.001*	.028	.000*	.062	.044	.123
ln(HUMAN_CAP)×HUMAN_CAP	.000*	.002*	.690	.883	.001*	.000*	.015	.821

Note: only significance values are reported

* denotes a significant term

Appendix D. Multicollinearity diagnostics

Table D-1 Multicollinearity diagnostics for nuclear power

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.659	1.516	.637	1.570	.632	1.583
NEIGHBOR	.768	1.302	.638	1.568	.631	1.584
STABILITY	.896	1.117	.563	1.777	.552	1.811
REGIME	.757	1.321	.620	1.613	.582	1.719
TIME_LAG	.914	1.094	.687	1.455	.575	1.738
PATENTS			.299	3.346*	.259	3.865*
TRADE			.741	1.350	.687	1.456
INVEST			.295	3.394*	.195	5.140*
SURFACE			.762	1.312	.736	1.359
GOV_SIZE					.627	1.595
HUMAN_CAP					.283	3.533
			Hypothesis 2			
DISSIMILARITY	.263	3.796*	.244	4.099*	.150	6.667*
NEIGHBOR	.870	1.149	.675	1.481	.657	1.521
STABILITY	.906	1.104	.525	1.904	.524	1.909
REGIME	.261	3.834*	.254	3.937*	.218	4.586*
TIME_LAG	.487	2.054	.386	2.592*	.228	4.387*
PATENTS			.291	3.439*	.259	3.867*
TRADE			.737	1.356	.685	1.460
INVEST			.299	3.350*	.191	5.246*
SURFACE			.762	1.313	.737	1.358
GOV_SIZE					.608	1.645
HUMAN_CAP					.175	5.701*
			Hypothesis 3			
LEADER	.615	1.626	.595	1.680	.532	1.879
NON-LEADER	.546	1.831	.524	1.909	.522	1.917
NEIGHBOR	.783	1.277	.636	1.572	.624	1.602
STABILITY	.914	1.094	.556	1.799	.550	1.820
REGIME	.772	1.296	.617	1.620	.585	1.709
TIME_LAG	.920	1.086	.680	1.470	.540	1.853
PATENTS			.294	3.399*	.248	4.026*
TRADE			.728	1.373	.651	1.537
INVEST			.288	3.468*	.192	5.212*
SURFACE			.746	1.341	.717	1.395
GOV_SIZE					.591	1.691
HUMAN_CAP					.244	4.100

*VIF > 2.5, **VIF > 10

Table D-2 Multicollinearity diagnostics for solar power

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.620	1.612	.611	1.637	.611	1.635
NEIGHBOR	.678	1.475	.592	1.689	.545	1.834
STABILITY	.921	1.086	.536	1.866	.371	2.696*
REGIME	.830	1.205	.665	1.505	.708	1.413
TIME_LAG	.658	1.520	.620	1.612	.586	1.707
PATENTS			.273	3.657	.226	4.418*
TRADE			.807	1.240	.766	1.305
INVEST			.309	3.241	.181	5.517*
SURFACE			.736	1.358	.645	1.551
GOV_SIZE					.596	1.678
HUMAN_CAP					.341	2.936*
			Hypothesis 2			
DISSIMILARITY	.219	4.565*	.214	4.663*	.203	4.916*
NEIGHBOR	.707	1.415	.608	1.644	.538	1.859
STABILITY	.930	1.076	.536	1.864	.361	2.767*
REGIME	.422	2.370*	.341	2.932*	.366	2.729*
TIME_LAG	.228	4.384*	.236	4.235*	.223	4.487*
PATENTS			.276	3.623*	.226	4.434*
TRADE			.808	1.238	.774	1.292
INVEST			.313	3.195*	.188	5.311*
SURFACE			.738	1.356	.665	1.503
GOV_SIZE					.596	1.679
HUMAN_CAP					.340	2.938*
			Hypothesis 3			
LEADER	.619	1.616	.569	1.757	.343	2.918*
NON-LEADER	.571	1.751	.554	1.805	.358	2.795*
NEIGHBOR	.698	1.433	.605	1.652	.548	1.824
STABILITY	.946	1.057	.509	1.966	.335	2.981*
REGIME	.739	1.353	.627	1.595	.684	1.462
TIME_LAG	.631	1.584	.613	1.630	.624	1.603
PATENTS			.266	3.757*	.226	4.421*
TRADE			.796	1.256	.740	1.351
INVEST			.296	3.377*	.179	5.572*
SURFACE			.725	1.379	.653	1.533
GOV_SIZE					.584	1.711
HUMAN_CAP					.333	3.003*

*VIF > 2.5, **VIF > 10

Table D-3 Multicollinearity diagnostics for wind power

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.590	1.696	.580	1.723	.615	1.626
NEIGHBOR	.661	1.512	.550	1.817	.563	1.777
STABILITY	.913	1.095	.514	1.945	.348	2.870*
REGIME	.803	1.245	.648	1.542	.691	1.447
TIME_LAG	.713	1.403	.671	1.490	.692	1.446
PATENTS			.275	3.634*	.245	4.084*
TRADE			.798	1.254	.751	1.331
INVEST			.306	3.267*	.193	5.191*
SURFACE			.718	1.393	.616	1.625
GOV_SIZE					.613	1.632
HUMAN_CAP					.338	2.955*
			Hypothesis 2			
DISSIMILARITY	.309	3.237*	.309	3.235*	.318	3.142*
NEIGHBOR	.761	1.314	.587	1.704	.562	1.780
STABILITY	.883	1.133	.488	2.049	.280	3.578*
REGIME	.509	1.964	.408	2.451	.421	2.375
TIME_LAG	.287	3.489*	.297	3.364*	.407	2.456
PATENTS			.261	3.828*	.246	4.059*
TRADE			.759	1.318	.756	1.323
INVEST			.309	3.241*	.179	5.582*
SURFACE			.703	1.423	.613	1.631
GOV_SIZE					.586	1.705
HUMAN_CAP					.322	3.104*
			Hypothesis 3			
LEADER	.628	1.593	.604	1.655	.406	2.464*
NON-LEADER	.659	1.516	.651	1.535	.533	1.878
NEIGHBOR	.719	1.391	.586	1.707	.557	1.794
STABILITY	.938	1.066	.492	2.031	.320	3.121*
REGIME	.740	1.352	.619	1.616	.596	1.678
TIME_LAG	.678	1.476	.658	1.521	.732	1.365
PATENTS			.267	3.742*	.245	4.086*
TRADE			.788	1.268	.731	1.369
INVEST			.303	3.300*	.198	5.054*
SURFACE			.708	1.412	.623	1.604
GOV_SIZE					.599	1.669
HUMAN_CAP					.317	3.158*

*VIF > 2.5, **VIF > 10

Table D-4 Multicollinearity diagnostics for marine power

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.697	1.435	.641	1.560	.598	1.671
NEIGHBOR	.808	1.238	.705	1.419	.654	1.530
STABILITY	.881	1.135	.567	1.764	.415	2.409*
REGIME	.784	1.275	.627	1.595	.603	1.657
TIME_LAG	.857	1.167	.690	1.450	.679	1.472
PATENTS			.295	3.395*	.260	3.843*
TRADE			.789	1.267	.684	1.463
INVEST			.294	3.400*	.208	4.817*
SURFACE			.750	1.334	.623	1.606
GOV_SIZE					.598	1.671
HUMAN_CAP					.293	3.418*
			Hypothesis 2			
DISSIMILARITY	.347	2.885*	.347	2.885*	.328	3.046*
NEIGHBOR	.891	1.123	.784	1.275	.700	1.429
STABILITY	.889	1.125	.569	1.757	.416	2.401
REGIME	.451	2.219	.367	2.724*	.298	3.358*
TIME_LAG	.357	2.800*	.342	2.925*	.354	2.825*
PATENTS			.295	3.391*	.258	3.872*
TRADE			.794	1.260	.698	1.432
INVEST			.313	3.190*	.215	4.644*
SURFACE			.750	1.334	.625	1.601
GOV_SIZE					.589	1.697
HUMAN_CAP					.287	3.489*
			Hypothesis 3			
LEADER	.928	1.077	.852	1.174	.643	1.556
NON-LEADER	.690	1.449	.666	1.502	.595	1.681
NEIGHBOR	.813	1.230	.717	1.395	.543	1.841
STABILITY	.886	1.129	.558	1.791	.386	2.588*
REGIME	.678	1.474	.571	1.752	.571	1.751
TIME_LAG	.876	1.142	.692	1.444	.721	1.387
PATENTS			.280	3.574*	.258	3.880*
TRADE			.780	1.282	.638	1.567
INVEST			.281	3.558*	.203	4.922*
SURFACE			.699	1.430	.549	1.822
GOV_SIZE					.575	1.740
HUMAN_CAP					.285	3.508*

*VIF > 2.5, **VIF > 10

Table D-5 Multicollinearity diagnostics for higher-speed rail

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.668	1.496	.651	1.536	.637	1.570
NEIGHBOR	.699	1.431	.623	1.605	.611	1.636
STABILITY	.871	1.148	.534	1.872	.384	2.605*
REGIME	.774	1.293	.624	1.603	.668	1.497
TIME_LAG	.877	1.140	.700	1.428	.745	1.341
PATENTS			.265	3.772*	.246	4.059*
TRADE			.763	1.311	.746	1.340
INVEST			.279	3.580*	.191	5.236*
SURFACE			.757	1.321	.693	1.443
GOV_SIZE					.590	1.696
HUMAN_CAP					.339	2.948*
			Hypothesis 2			
DISSIMILARITY	.261	3.835*	.237	4.219*	.122	8.220*
NEIGHBOR	.810	1.234	.663	1.508	.606	1.649
STABILITY	.879	1.138	.535	1.868	.384	2.601*
REGIME	.289	3.455*	.223	4.492*	.113	8.869*
TIME_LAG	.346	2.889*	.319	3.140*	.311	3.218*
PATENTS			.266	3.765*	.248	4.033*
TRADE			.763	1.310	.745	1.342
INVEST			.285	3.506*	.184	5.423*
SURFACE			.757	1.321	.693	1.442
GOV_SIZE					.579	1.728
HUMAN_CAP					.338	2.957*
			Hypothesis 3			
LEADER	.769	1.301	.717	1.395	.494	2.025
NON-LEADER	.638	1.568	.650	1.539	.460	2.174
NEIGHBOR	.696	1.437	.625	1.601	.603	1.658
STABILITY	.852	1.173	.504	1.985	.362	2.759*
REGIME	.725	1.379	.600	1.666	.656	1.525
TIME_LAG	.882	1.133	.691	1.448	.747	1.338
PATENTS			.264	3.785*	.244	4.098*
TRADE			.749	1.335	.715	1.398
INVEST			.271	3.696*	.193	5.193*
SURFACE			.749	1.335	.667	1.500
GOV_SIZE					.566	1.768
HUMAN_CAP					.307	3.254*

*VIF > 2.5, **VIF > 10

Table D-6 Multicollinearity diagnostics for high-speed rail

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.685	1.461	.667	1.499	.625	1.599
NEIGHBOR	.747	1.340	.710	1.409	.672	1.489
STABILITY	.885	1.131	.539	1.856	.395	2.530*
REGIME	.826	1.211	.629	1.590	.672	1.489
TIME_LAG	.856	1.169	.688	1.455	.724	1.382
PATENTS			.273	3.667*	.242	4.136*
TRADE			.764	1.309	.748	1.338
INVEST			.283	3.531*	.196	5.107*
SURFACE			.749	1.335	.660	1.515
GOV_SIZE					.592	1.690
HUMAN_CAP					.337	2.964*
			Hypothesis 2			
DISSIMILARITY	.356	2.807*	.327	3.055*	.212	4.725*
NEIGHBOR	.883	1.133	.791	1.265	.673	1.485
STABILITY	.908	1.101	.539	1.857	.392	2.549*
REGIME	.421	2.376	.315	3.179*	.204	4.897*
TIME_LAG	.396	2.525*	.348	2.873*	.330	3.033*
PATENTS			.273	3.668*	.242	4.135*
TRADE			.764	1.309	.744	1.345
INVEST			.288	3.473*	.195	5.138*
SURFACE			.750	1.333	.667	1.499
GOV_SIZE					.585	1.711
HUMAN_CAP					.336	2.979*
			Hypothesis 3			
LEADER	.946	1.057	.909	1.100	.887	1.127
NON-LEADER	.661	1.512	.640	1.561	.612	1.634
NEIGHBOR	.726	1.378	.699	1.430	.655	1.528
STABILITY	.877	1.140	.538	1.858	.387	2.584*
REGIME	.788	1.270	.617	1.621	.649	1.540
TIME_LAG	.859	1.164	.693	1.444	.736	1.358
PATENTS			.264	3.784*	.238	4.200*
TRADE			.762	1.313	.746	1.341
INVEST			.274	3.647*	.193	5.186*
SURFACE			.731	1.368	.639	1.565
GOV_SIZE					.593	1.685
HUMAN_CAP					.333	3.006*

*VIF > 2.5, **VIF > 10

Table D-7 Multicollinearity diagnostics for telecommunication satellites

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.629	1.589	.564	1.773	.743	1.346
NEIGHBOR	.581	1.720	.538	1.858	.604	1.656
STABILITY	.872	1.147	.539	1.856	.396	2.527*
REGIME	.873	1.145	.587	1.703	.584	1.713
TIME_LAG	.733	1.365	.631	1.586	.739	1.354
PATENTS			.261	3.830*	.220	4.551*
TRADE			.754	1.327	.745	1.343
INVEST			.252	3.971*	.207	4.832*
SURFACE			.756	1.323	.689	1.451
GOV_SIZE					.604	1.656
HUMAN_CAP					.340	2.941*
			Hypothesis 2			
DISSIMILARITY	.207	4.821*	.254	3.941*	.636	1.573
NEIGHBOR	.723	1.383	.652	1.533	.580	1.725
STABILITY	.875	1.143	.536	1.866	.385	2.599*
REGIME	.707	1.414	.495	2.022	.556	1.800
TIME_LAG	.202	4.941*	.236	4.242*	.603	1.657
PATENTS			.272	3.682*	.212	4.716*
TRADE			.759	1.318	.747	1.339
INVEST			.282	3.544*	.210	4.768*
SURFACE			.755	1.324	.693	1.442
GOV_SIZE					.613	1.631
HUMAN_CAP					.340	2.939*
			Hypothesis 3			
LEADER	.731	1.368	.643	1.556	.334	2.995*
NON-LEADER	.578	1.731	.572	1.749	.341	2.933*
NEIGHBOR	.685	1.459	.632	1.582	.617	1.622
STABILITY	.875	1.143	.507	1.971	.366	2.729*
REGIME	.836	1.195	.583	1.715	.609	1.642
TIME_LAG	.671	1.491	.591	1.692	.716	1.396
PATENTS			.263	3.798*	.214	4.679*
TRADE			.742	1.348	.729	1.372
INVEST			.257	3.897*	.202	4.942*
SURFACE			.746	1.340	.667	1.499
GOV_SIZE					.614	1.629
HUMAN_CAP					.313	3.193*

*VIF > 2.5, **VIF > 10

Table D-8 Multicollinearity diagnostics for telecommunication satellites

	Model 2		Model 3		Model 4	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
			Hypothesis 1			
ALLY	.640	1.562	.628	1.594	.635	1.575
NEIGHBOR	.688	1.454	.619	1.616	.583	1.714
STABILITY	.878	1.140	.535	1.870	.382	2.619*
REGIME	.788	1.269	.617	1.620	.663	1.508
TIME_LAG	.888	1.126	.701	1.427	.751	1.332
PATENTS			.260	3.845*	.237	4.221*
TRADE			.763	1.311	.747	1.338
INVEST			.280	3.575*	.192	5.197*
SURFACE			.757	1.321	.689	1.452
GOV_SIZE					.591	1.693
HUMAN_CAP					.340	2.939*
			Hypothesis 2			
DISSIMILARITY	.379	2.636*	.327	3.059*	.132	7.579*
NEIGHBOR	.830	1.205	.683	1.463	.577	1.733
STABILITY	.880	1.136	.534	1.874	.382	2.621*
REGIME	.431	2.321	.293	3.408*	.118	8.450*
TIME_LAG	.453	2.207	.403	2.480	.476	2.099
PATENTS			.260	3.842*	.241	4.148*
TRADE			.764	1.310	.748	1.336
INVEST			.288	3.469*	.186	5.368*
SURFACE			.757	1.321	.690	1.450
GOV_SIZE					.576	1.735
HUMAN_CAP					.341	2.931*
			Hypothesis 3			
LEADER	.727	1.375	.606	1.650	.327	3.054*
NON-LEADER	.620	1.614	.571	1.750	.311	3.212*
NEIGHBOR	.786	1.272	.667	1.500	.584	1.712
STABILITY	.882	1.134	.501	1.997	.359	2.782*
REGIME	.748	1.336	.582	1.719	.653	1.532
TIME_LAG	.792	1.263	.645	1.551	.697	1.434
PATENTS			.253	3.950*	.237	4.228*
TRADE			.753	1.328	.726	1.377
INVEST			.277	3.616*	.178	5.608*
SURFACE			.735	1.360	.653	1.532
GOV_SIZE					.576	1.736
HUMAN_CAP					.306	3.267*

*VIF > 2.5, **VIF > 10

Appendix E. Correlation matrices

Table E-1 Correlation matrix of nuclear power variables

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	-.310	1												
LEADER	.567	-.252	1											
NON-LEADER	.726	-.246	.610	1										
NEIGHBOR	.457	-.140	.267	.398	1									
STABILITY	.288	-.086	.048	.149	.208	1								
REGIME	.451	-.698	.296	.367	.308	.245	1							
TIME_LAG	.238	.315	.041	.124	.202	.102	.237	1						
PATENTS	.467	-.425	.250	.307	.505	.586	.529	.109	1					
TRADE	.072	.061	-.065	.026	.002	.061	.057	.285	-.013	1				
INVEST	.478	-.199	.240	.348	.397	.542	.473	.451	.679	.342	1			
SURFACE	.151	-.040	.031	.158	.268	.295	.023	-.038	.313	-.241	.081	1		
GOV_SIZE	.154	-.159	.041	.075	.127	.128	.182	.004	.132	.063	.408	-.147	1	
HUMAN_CAP	.486	-.426	.401	.420	.407	.371	.555	.455	.614	.302	.791	.091	.374	1

Table E-2 Correlation matrix of solar power variables

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	.232	1												
LEADER	.559	-.063	1											
NON-LEADER	.652	.250	.516	1										
NEIGHBOR	.459	.359	.222	.356	1									
STABILITY	.239	.020	.079	.082	.166	1								
REGIME	.395	-.308	.451	.348	.243	.187	1							
TIME_LAG	.479	.730	.115	.449	.499	.049	.231	1						
PATENTS	.313	-.092	.276	.175	.361	.592	.501	.113	1					
TRADE	.061	.138	-.020	.021	.034	.035	.024	.176	.000	1				
INVEST	.419	.072	.359	.306	.304	.576	.445	.242	.727	.278	1			
SURFACE	.104	-.029	.070	.085	.247	.281	.041	-.020	.314	-.225	.091	1		
GOV_SIZE	.052	-.133	.016	-.044	-.057	.108	.178	-.057	.129	.082	.400	-.144	1	
HUMAN_CAP	.422	.057	.406	.301	.318	.376	.547	.336	.635	.267	.775	.082	.353	1

Table E-3 Correlation matrix of wind power variables

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	.138	1												
LEADER	.592	-.019	1											
NON-LEADER	.583	.267	.485	1										
NEIGHBOR	.522	.250	.350	.319	1									
STABILITY	.260	.087	.057	.052	.159	1								
REGIME	.416	-.237	.451	.271	.276	.203	1							
TIME_LAG	.450	.684	.286	.443	.459	.049	.287	1						
PATENTS	.360	-.083	.258	.100	.391	.589	.512	.108	1					
TRADE	.090	.108	.019	.018	.065	.033	.019	.169	-.012	1				
INVEST	.469	.050	.348	.235	.382	.565	.451	.239	.716	.277	1			
SURFACE	.103	.002	.032	.075	.231	.290	.034	-.025	.312	-.231	.089	1		
GOV_SIZE	.113	-.182	.027	.015	.071	.119	.179	-.030	.133	.069	.405	-.145	1	
HUMAN_CAP	.480	.087	.454	.293	.455	.366	.542	.385	.624	.268	.770	.086	.365	1

Table E-4 Correlation matrix of marine power variables

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	-.053	1												
LEADER	.143	.117	1											
NON-LEADER	.755	-.137	-.021	1										
NEIGHBOR	.393	.068	.207	.294	1									
STABILITY	.263	.015	.018	.247	.272	1								
REGIME	.410	-.348	-.117	.513	.175	.209	1							
TIME_LAG	.298	.579	.048	.215	.165	.107	.319	1						
PATENTS	.397	-.169	-.079	.401	.394	.557	.520	.136	1					
TRADE	.013	.170	.048	-.080	-.061	-.007	-.016	.217	-.058	1				
INVEST	.455	.100	.058	.401	.238	.521	.444	.424	.654	.253	1			
SURFACE	.087	-.032	.095	.154	.181	.334	.027	-.028	.338	-.254	.089	1		
GOV_SIZE	.141	-.104	-.009	.030	.028	.163	.131	.014	.079	.027	.400	-.159	1	
HUMAN_CAP	.485	-.029	.093	.470	.258	.379	.562	.467	.635	.245	.799	.106	.335	1

Table E-5 Correlation matrix of higher-speed rail varialbes

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	-.232	1												
LEADER	.525	-.258	1											
NON-LEADER	.787	-.162	.403	1										
NEIGHBOR	.500	-.126	.216	.484	1									
STABILITY	.282	-.105	.072	.304	.306	1								
REGIME	.402	-.574	.374	.352	.318	.242	1							
TIME_LAG	.251	.438	.101	.115	.244	.089	.298	1						
PATENTS	.451	-.335	.265	.465	.506	.586	.533	.111	1					
TRADE	.102	.114	-.027	.047	.131	.049	.051	.254	-.011	1				
INVEST	.485	-.112	.318	.411	.494	.549	.481	.416	.683	.324	1			
SURFACE	.077	-.043	.003	.167	.206	.296	.021	-.035	.311	-.241	.083	1		
GOV_SIZE	.208	-.206	.044	.207	.114	.128	.182	.004	.133	.063	.408	-.147	1	
HUMAN_CAP	.468	-.219	.390	.396	.458	.370	.554	.457	.620	.300	.791	.090	.374	1

Table E-6 Correlation matrix of high-speed rail variables

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	-.087	1												
LEADER	.093	.244	1											
NON-LEADER	.854	-.110	.107	1										
NEIGHBOR	.480	.011	.143	.493	1									
STABILITY	.284	-.075	.013	.312	.229	1								
REGIME	.322	-.444	-.070	.359	.227	.242	1							
TIME_LAG	.292	.506	.130	.231	.244	.089	.298	1						
PATENTS	.390	-.264	-.066	.451	.367	.586	.533	.111	1					
TRADE	.129	.124	.047	.085	.134	.049	.051	.254	-.011	1				
INVEST	.452	-.043	.089	.466	.390	.549	.481	.416	.683	.324	1			
SURFACE	.073	-.039	.019	.158	.077	.296	.021	-.035	.311	-.241	.083	1		
GOV_SIZE	.224	-.185	-.027	.214	.091	.128	.182	.004	.133	.063	.408	-.147	1	
HUMAN_CAP	.435	-.109	.094	.430	.329	.370	.554	.457	.620	.300	.791	.090	.374	1

Table E-7 Correlation matrix of telecommunication satellites varialbes

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	.407	1												
LEADER	.526	.137	1											
NON-LEADER	.714	.463	.487	1										
NEIGHBOR	.592	.470	.265	.445	1									
STABILITY	.201	.086	.081	.127	.265	1								
REGIME	.080	.018	.231	.219	.113	.244	1							
TIME_LAG	.385	.854	.155	.467	.435	.100	.273	1						
PATENTS	.162	-.024	.203	.133	.333	.586	.533	.111	1					
TRADE	.124	.229	-.010	.077	.104	.060	.056	.285	-.011	1				
INVEST	.438	.328	.350	.370	.436	.543	.471	.454	.683	.342	1			
SURFACE	.018	-.041	-.007	.067	.160	.295	.021	-.038	.311	-.242	.080	1		
GOV_SIZE	.276	-.020	.121	.137	.073	.128	.182	.004	.133	.063	.408	-.147	1	
HUMAN_CAP	.304	.274	.367	.313	.346	.370	.554	.457	.620	.300	.791	.090	.374	1

Table E-8 Correlation matrix of meteorological satellites variables

	PRIOR	SIM	LEAD	NON_LEAD	NEIGH	STAB	REG	TIME	PAT	TRAD	INV	SUR	GOVS	HUM
ALLY	1													
DISSIMILARITY	-.217	1												
LEADER	.472	-.266	1											
NON-LEADER	.699	-.107	.441	1										
NEIGHBOR	.525	-.103	.216	.368	1									
STABILITY	.271	-.068	.081	.172	.295	1								
REGIME	.403	-.493	.341	.378	.288	.244	1							
TIME_LAG	.262	.452	.000	.364	.229	.100	.273	1						
PATENTS	.444	-.319	.282	.274	.513	.586	.533	.111	1					
TRADE	.100	.113	-.071	.091	.066	.060	.056	.285	-.011	1				
INVEST	.487	-.070	.269	.407	.451	.543	.471	.454	.683	.342	1			
SURFACE	.076	-.044	.036	.133	.191	.295	.021	-.038	.311	-.242	.080	1		
GOV_SIZE	.205	-.172	.015	.057	.096	.128	.182	.004	.133	.063	.408	-.147	1	
HUMAN_CAP	.466	-.216	.391	.455	.425	.370	.554	.457	.620	.300	.791	.090	.374	1

Appendix F. Full regression results and model quality indicators

Table F-1 Logistic regression results for hypothesis 1, nuclear

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.225	.000	1.252	1.231	1.273	.040	.000	1.041	1.020	1.062	.041	.002	1.042	1.015	1.068	.049	.004	1.050	1.016	1.085
NEIGHBOR						.658	.000	1.932	1.817	2.054	.186	.000	1.204	1.113	1.302	.045	.479	1.046	.924	1.184
STABLITY						.016	.000	1.016	1.014	1.019	-.012	.000	.988	.984	.992	-.003	.390	.997	.989	1.004
REGIME						.097	.000	1.102	1.089	1.116	.076	.000	1.079	1.054	1.105	.350	.000	1.418	1.268	1.587
TIME_LAG						.002	.379	1.002	.997	1.007	.027	.000	1.027	1.018	1.038	-.089	.000	.915	.885	.946
PATENTS											.639	.000	1.894	1.788	2.006	.430	.000	1.538	1.401	1.688
TRADE											-.003	.036	.997	.994	1.000	.007	.002	1.007	1.002	1.011
INVEST											-.462	.000	.630	.570	.697	-.496	.000	.609	.495	.749
SURFACE											.000	.019	1.000	1.000	1.000	.000	.002	1.000	1.000	1.000
GOV_SIZE																-.047	.000	.954	.930	.979
HUMAN_CAP																.023	.032	1.024	1.002	1.046
Intercept	-2.281	.000	.102			-3.288	.000	.037			-.593	.143	.553			3.126	.002	22.792		
Valid N (listwise)			7772					7635					4812					998		
-2LL			5941.241					4636.612					2420.744					816.411		
Omnibus χ^2/df/Sig.	804.358		1		.000	2051.885		5		.000	2385.687		9		.000	535.910		11		.000
H-L χ^2/df/Sig.	122.297		3		.000	77.050		8		.000	37.078		8		.000	14.975		8		.060
Nagelkere R^2			.169					.404					.619					.560		

Table F-2 Logistic regression results for hypothesis 2, nuclear power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
DISSIMILARITY	-.006	.000	.994	.993	.994	-.001	.142	.999	.998	1.000	.000	.891	1.000	.998	1.002	-.016	.010	.984	.972	.996
NEIGHBOR						.699	.000	2.013	1.896	2.136	.212	.000	1.236	1.143	1.337	.061	.329	1.063	.941	1.201
STABLITY						.017	.000	1.017	1.014	1.019	-.013	.000	.987	.983	.991	-.005	.155	.995	.987	1.002
REGIME						.091	.000	1.096	1.072	1.120	.079	.000	1.083	1.039	1.128	.139	.164	1.150	.945	1.399
TIME_LAG						.006	.031	1.006	1.001	1.011	.028	.000	1.028	1.018	1.038	-.100	.000	.905	.874	.938
PATENTS											.629	.000	1.876	1.772	1.985	.443	.000	1.558	1.419	1.710
TRADE											-.003	.031	.997	.994	1.000	.007	.002	1.007	1.003	1.011
INVEST											-.418	.000	.658	.598	.725	-.420	.000	.657	.537	.804
SURFACE											.000	.008	1.000	1.000	1.000	.000	.001	1.000	1.000	1.000
GOV_SIZE																-.046	.000	.955	.931	.979
HUMAN_CAP																.021	.054	1.021	1.000	1.044
Intercept	-.725	.000	.484			-3.193	.000	.041			-.939	.029	.391			6.065	.001	430.50		
Valid N (listwise)			7635					7635					4812					998		
-2LL			6216.400					4649.492					2430.611					818.260		
Omnibus χ^2/df/Sig.	472.098		1	.000		2039.006		5	.000		2375.820		9	.000		534.060		11	.000	
H-L χ^2/df/Sig.	316.988		8	.000		79.347		8	.000		44.712		8	.000		44.571		8	.000	
Nagelkere R^2			.103					.402					.617					.558		

Table F-3 Logistic regression results for hypothesis 3, nuclear power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Lower
LEADER	.680	.000	1.974	1.673	2.329	.887	.000	2.427	1.990	2.961	.836	.000	2.307	1.684	3.159	-.267	.448	.766	.384	1.526
NON-LEADER	1.038	.000	2.825	2.408	3.314	-.199	.048	.820	.674	.998	.048	.752	1.050	.778	1.417	.993	.004	2.700	1.370	5.322
NEIGHBOR						.674	.000	1.962	1.844	2.087	.198	.000	1.219	1.127	1.317	.007	.910	1.007	.888	1.143
STABLITY						.018	.000	1.018	1.016	1.020	-.008	.000	.992	.988	.996	-.004	.362	.996	.989	1.004
REGIME						.092	.000	1.096	1.083	1.110	.070	.000	1.073	1.048	1.098	.383	.000	1.466	1.306	1.646
TIME_LAG						.004	.103	1.004	.999	1.009	.034	.000	1.034	1.024	1.045	-.085	.000	.918	.888	.949
PATENTS											.656	.000	1.926	1.815	2.044	.454	.000	1.575	1.431	1.733
TRADE											-.001	.295	.999	.996	1.001	.008	.000	1.008	1.003	1.012
INVEST											-.518	.000	.596	.537	.661	-.517	.000	.597	.484	.736
SURFACE											.000	.178	1.000	1.000	1.000	.000	.003	1.000	1.000	1.000
GOV_SIZE																-.047	.000	.954	.930	.979
HUMAN_CAP																.024	.034	1.024	1.002	1.048
Intercept	-2.508	.000	.081			-3.718	.000	.024			-.850	.035	.427			2.539	.007	12.666		
Valid N (listwise)			7772					7635					4812					998		
-2LL			6165.522					4561.069					2382.069					809.363		
Omnibus χ^2/df/Sig.	580.077		2	.000		2127.429		6	.000		2424.362		10	.000		542.957		12	.000	
H-L χ^2/df/Sig.	91.005		2	.000		55.072		8	.000		21.187		8	.007		22.466		8	.004	
Nagelkere R^2			.124					.417					.627					.565		

Table F-4 Logistic regression results for hypothesis 1, solar power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.146	.000	1.157	1.142	1.172	-.008	.388	.992	.976	1.010	.002	.878	1.002	.982	1.022	.015	.282	1.015	.988	1.044
NEIGHBOR						.490	.000	1.633	1.513	1.763	.353	.000	1.423	1.304	1.554	.395	.000	1.484	1.267	1.738
STABLITY						.026	.000	1.026	1.023	1.030	.011	.000	1.012	1.007	1.016	.029	.000	1.030	1.020	1.039
REGIME						.086	.000	1.090	1.072	1.108	.020	.073	1.020	.998	1.042	-.016	.488	.984	.940	1.030
TIME_LAG						.139	.000	1.149	1.130	1.169	.169	.000	1.184	1.159	1.209	.120	.000	1.127	1.082	1.174
PATENTS											.340	.000	1.404	1.333	1.479	.215	.000	1.240	1.137	1.351
TRADE											-.008	.000	.992	.990	.995	-.013	.000	.987	.983	.992
INVEST											-.129	.006	.879	.802	.963	.186	.082	1.205	.977	1.486
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																-.056	.000	.946	.919	.973
HUMAN_CAP																-.014	.167	.986	.966	1.006
Intercept	-1.800	.000	.165			-5.130	.000	.006			-4.067	.000	.017			-3.717	.000	.024		
Valid N (listwise)			4245					4168					3344					957		
-2LL			3964.436					2771.547					2186.664					780.871		
Omnibus χ^2/df/Sig.	628.398		1		.000	1768.598		5		.000	1711.791		9		.000	545.511		11		.000
H-L χ^2/df/Sig.	60.839		3		.000	19.918		8		.011	15.372		8		.052	14.716		8		.065
Nagelkere R^2			.209					.522					.582					.579		

Table F-5 Logistic regression results for hypothesis 2, solar power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
DISSIMILARITY	.002	.000	1.002	1.002	1.002	.001	.000	1.001	1.001	1.002	.001	.052	1.001	1.000	1.002	.000	.605	1.000	.999	1.002
NEIGHBOR						.465	.000	1.592	1.478	1.714	.342	.000	1.407	1.290	1.535	.400	.000	1.492	1.272	1.750
STABLITY						.024	.000	1.024	1.021	1.027	.011	.000	1.011	1.006	1.015	.028	.000	1.029	1.019	1.039
REGIME						.126	.000	1.134	1.104	1.165	.047	.007	1.048	1.013	1.085	.003	.920	1.003	.938	1.074
TIME_LAG						.097	.000	1.102	1.075	1.129	.148	.000	1.160	1.127	1.194	.113	.000	1.120	1.053	1.192
PATENTS											.341	.000	1.407	1.336	1.481	.211	.000	1.235	1.133	1.346
TRADE											-.008	.000	.992	.990	.995	-.013	.000	.987	.983	.992
INVEST											-.149	.001	.862	.787	.944	.205	.052	1.228	.998	1.509
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																-.056	.000	.945	.918	.973
HUMAN_CAP																-.014	.178	.986	.967	1.006
Intercept	-1.790	.000	.167			-4.950	.000	.007			-3.847	.000	.021			-3.949	.000	.019		
Valid N (listwise)			4168					4168					3334					957		
-2LL			4260.608					2756.775					2182.933					781.762		
Omnibus χ^2/df/Sig.	279.537		1		.000	1783.371		5		.000	1715.522		9		.000	544.619		11		.000
H-L χ^2/df/Sig.	95.478		8		.000	18.625		8		.017	16.077		8		.041	17.377		8		.026
Nagelkere R^2			.098					.526					.583					.579		

Table F-6 Logistic regression results for hypothesis 3, solar power

Variable	Model 1					Model 2					Model 3					Model 4				
	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Lower
LEADER	.613	.000	1.846	1.559	2.186	.555	.000	1.741	1.383	2.193	.244	.085	1.276	.967	1.685	.509	.109	1.664	.893	3.099
NON-LEADER	.814	.000	2.257	1.905	2.674	-.647	.000	.524	.413	.664	-.305	.032	.737	.558	.975	-.220	.470	.802	.442	1.458
NEIGHBOR						.500	.000	1.649	1.527	1.781	.365	.000	1.441	1.320	1.574	.407	.000	1.502	1.283	1.759
STABLITY						.025	.000	1.026	1.022	1.029	.012	.000	1.012	1.007	1.016	.030	.000	1.031	1.021	1.040
REGIME						.077	.000	1.080	1.063	1.098	.018	.082	1.019	.998	1.040	-.022	.364	.978	.934	1.026
TIME_LAG						.147	.000	1.159	1.140	1.178	.174	.000	1.189	1.165	1.214	.131	.000	1.140	1.095	1.186
PATENTS											.328	.000	1.388	1.317	1.463	.212	.000	1.236	1.134	1.348
TRADE											-.008	.000	.992	.989	.994	-.013	.000	.987	.983	.992
INVEST											-.118	.012	.888	.810	.974	.174	.107	1.190	.963	1.470
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																-.050	.001	.951	.923	.979
HUMAN_CAP																-.017	.110	.984	.964	1.004
Intercept	-1.830	.000	.160			-5.188	.000	.006			-4.176	.000	.015			-3.737	.000	.024		
Valid N (listwise)			4245					4168					3344					957		
-2LL			4313.252					2737.101					2181.451					778.958		
Omnibus χ^2/df/Sig.	279.583		2	.000		1803.044		6	.000		1717.003		10	.000		547.424		12	.000	
H-L χ^2/df/Sig.	.000		2	1.000		23.538		8	.003		12.965		8	.113		13.036		8	.111	
Nagelkere R^2			.097					.530					.583					.581		

Table F-7 Logistic regression results for hypothesis 1, wind power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.173	.000	1.188	1.174	1.203	.019	.023	1.019	1.003	1.036	.039	.000	1.040	1.019	1.060	.048	.001	1.049	1.020	1.078
NEIGHBOR						.431	.000	1.539	1.432	1.655	.135	.002	1.145	1.051	1.247	-.106	.196	.900	.766	1.056
STABLITY						.028	.000	1.028	1.025	1.032	.005	.025	1.005	1.001	1.010	.003	.438	1.003	.995	1.012
REGIME						.132	.000	1.141	1.123	1.160	.042	.000	1.043	1.022	1.065	-.064	.002	.938	.901	.977
TIME_LAG						.118	.000	1.126	1.111	1.140	.170	.000	1.186	1.164	1.207	.123	.000	1.131	1.094	1.170
PATENTS											.362	.000	1.436	1.365	1.511	.322	.000	1.379	1.257	1.514
TRADE											-.008	.000	.992	.990	.995	-.005	.038	.995	.991	1.000
INVEST											.096	.036	1.100	1.006	1.203	-.030	.766	.971	.799	1.180
SURFACE											.000	.729	1.000	1.000	1.000	.001	.005	1.001	1.000	1.001
GOV_SIZE																.015	.263	1.015	.989	1.041
HUMAN_CAP																.064	.000	1.066	1.041	1.091
Intercept	-1.941	.000	.144			-5.512	.000	.004			-7.416	.000	.001			-8.660	.000	.000		
Valid N (listwise)			5043					4953					3857					980		
-2LL			4425.514					2993.374					2216.943					718.731		
Omnibus χ^2/df/Sig.	1047.196		1		.000	2414.520		5		.000	2396.275		9		.000	570.025		11		.000
H-L χ^2/df/Sig.	14.239		4		.007	18.885		8		.015	10.646		8		.223	47.295		8		.000
Nagelkere R^2			.283					.581					.663					.603		

Table F-8 Logistic regression results for hypothesis 2, wind power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Upper	B	Sig.	e^B	95% CI for e^B Lower	Lower
DISSIMILARITY	.001	.000	1.001	1.001	1.001	.000	.159	1.000	.999	1.000	-.002	.000	.998	.997	.999	-.002	.026	.998	.997	1.000
NEIGHBOR						.490	.000	1.632	1.519	1.754	.197	.000	1.218	1.114	1.331	.017	.845	1.017	.859	1.205
STABLITY						.029	.000	1.029	1.025	1.033	.005	.022	1.005	1.001	1.010	.005	.332	1.005	.995	1.014
REGIME						.128	.000	1.137	1.109	1.166	-.001	.931	.999	.968	1.030	-.101	.001	.904	.852	.958
TIME_LAG						.130	.000	1.139	1.119	1.160	.212	.000	1.236	1.206	1.266	.166	.000	1.180	1.125	1.239
PATENTS											.375	.000	1.455	1.378	1.537	.344	.000	1.411	1.278	1.559
TRADE											-.006	.000	.994	.991	.998	-.007	.003	.993	.988	.998
INVEST											.164	.000	1.178	1.074	1.292	.071	.509	1.074	.869	1.328
SURFACE											.000	.575	1.000	1.000	1.000	.000	.050	1.000	1.000	1.001
GOV_SIZE																.014	.310	1.014	.987	1.041
HUMAN_CAP																.050	.000	1.051	1.027	1.076
Intercept	-1.421	.000	.241			-5.605	.000	.004			-8.449	.000	.000			-8.786	.000	.000		
Valid N (listwise)			4625					4263					3643					936		
-2LL			5069.151					2819.779					2060.463					684.128		
Omnibus χ^2/df/Sig.	78.485		1		.000	2326.734		5		.000	2340.224		9		.000	534.441		11		.000
H-L χ^2/df/Sig.	381.514		8		.000	26.114		8		.001	11.598		8		.170	49.938		8		.000
Nagelkere R^2			.025					.589					.676					.598		

Table F-9 Logistic regression results for hypothesis 3, wind power

Variable	Model 1					Model 2					Model 3					Model 4				
	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
LEADER	1.347	.000	3.847	3.289	4.499	.451	.000	1.570	1.253	1.968	.092	.495	1.096	.842	1.427	-.382	.183	.683	.389	1.197
NON-LEADER	.348	.000	1.416	1.208	1.659	-.453	.000	.636	.509	.795	.097	.463	1.102	.850	1.430	.733	.006	2.082	1.238	3.501
NEIGHBOR						.453	.000	1.573	1.466	1.688	.176	.000	1.192	1.096	1.297	-.072	.367	.930	.795	1.089
STABLITY						.028	.000	1.029	1.025	1.032	.005	.027	1.005	1.001	1.010	.000	.932	1.000	.992	1.009
REGIME						.129	.000	1.137	1.119	1.156	.053	.000	1.054	1.033	1.076	-.030	.210	.970	.926	1.017
TIME_LAG						.126	.000	1.134	1.120	1.149	.177	.000	1.194	1.173	1.215	.133	.000	1.143	1.104	1.182
PATENTS											.353	.000	1.423	1.352	1.498	.325	.000	1.384	1.260	1.519
TRADE											-.008	.000	.992	.990	.995	-.005	.045	.995	.991	1.000
INVEST											.131	.004	1.140	1.044	1.245	.032	.744	1.033	.851	1.254
SURFACE											.000	.610	1.000	1.000	1.000	.001	.006	1.001	1.000	1.001
GOV_SIZE																.009	.484	1.010	.983	1.037
HUMAN_CAP																.068	.000	1.070	1.045	1.096
Intercept	-1.944	.000	.143			-5.567	.000	.004			-7.961	.000	.000			-10.01	.000	.000		
Valid N (listwise)			5043					4953					3857					980		
-2LL			4968.927					2977.166					2229.943					722.461		
Omnibus χ^2/df/Sig.	503.783		2	.000		2430.729		6	.000		2383.274		10	.000		566.295		12	.000	
H-L χ^2/df/Sig.	15.936		2	.000		19.974		8	.010		7.968		8	.437		35.372		8	.000	
Nagelkere R^2			.144					.584					.661					.600		

Table F-10 Logistic regression results for hypothesis 1, marine power

Variable	Model 1					Model 2					Model 3					Model 4				
	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.505	.000	1.657	1.506	1.823	.278	.000	1.321	1.155	1.510	.444	.000	1.559	1.317	1.845	-.101	.535	.903	.656	1.245
NEIGHBOR						-.151	.492	.859	.558	1.323	-1.816	.000	.163	.095	.280	-.731	.037	.481	.242	.957
STABLITY						.015	.000	1.015	1.011	1.020	-.019	.000	.981	.976	.987	-.069	.000	.933	.913	.954
REGIME						.031	.036	1.032	1.002	1.063	-.128	.000	.879	.837	.924	1.247	.001	3.480	1.650	7.342
TIME_LAG						.021	.009	1.021	1.005	1.037	.012	.284	1.012	.990	1.035	.105	.046	1.111	1.002	1.232
PATENTS											.556	.000	1.743	1.586	1.916	.545	.000	1.725	1.284	2.316
TRADE											-.005	.108	.995	.989	1.001	-.026	.008	.974	.956	.993
INVEST											.041	.723	1.042	.830	1.308	2.166	.000	8.720	3.748	20.288
SURFACE											.000	.000	1.000	1.000	1.000	.001	.000	1.001	1.001	1.001
GOV_SIZE																.106	.012	1.112	1.024	1.207
HUMAN_CAP																.005	.885	1.005	.939	1.076
Intercept	-4.010	.000	.018			-4.967	.000	.007			-7.601	.000	.000			-54.28	.535	.903	.656	1.245
Valid N (listwise)			5368					5294					3889					826		
-2LL			1199.827					1127.005					674.221					190.804		
Omnibus χ^2/df/Sig.	79.137		1		.000	148.129		5		.000	517.206		9		.000	229.138		11		.000
H-L χ^2/df/Sig.	21.522		1		.000	15.857		8		.044	4.077		8		.850	9.002		8		.342
Nagelkere R^2			.069					.129					.472					.608		

Table F-11 Logistic regression results for hypothesis 2, marine power

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
DISSIMILARITY	.004	.363	1.004	.995	1.014	.006	.408	1.006	.991	1.022	-.008	.433	.992	.974	1.011	.017	.831	1.017	.869	1.192
NEIGHBOR						.142	.471	1.152	.784	1.693	-1.233	.000	.291	.181	.469	-.791	.026	.453	.226	.911
STABLITY						.015	.000	1.015	1.011	1.020	-.017	.000	.984	.978	.989	-.067	.000	.936	.917	.955
REGIME						.058	.004	1.060	1.019	1.102	-.115	.000	.891	.840	.946	1.183	.001	3.264	1.576	6.758
TIME_LAG						.024	.021	1.024	1.004	1.045	.027	.033	1.028	1.002	1.054	.077	.184	1.080	.964	1.209
PATENTS											.506	.000	1.659	1.521	1.809	.515	.000	1.674	1.267	2.211
TRADE											-.004	.138	.996	.991	1.001	-.026	.009	.975	.956	.994
INVEST											.102	.344	1.107	.896	1.368	2.120	.000	8.331	3.559	19.502
SURFACE											.000	.000	1.000	1.000	1.000	.001	.000	1.001	1.001	1.001
GOV_SIZE																.099	.017	1.104	1.018	1.197
HUMAN_CAP																.003	.943	1.003	.936	1.074
Intercept	-3.711	.000	.024			-5.134	.000	.006			-8.042	.000	.000			-51.84	.000	.000		
Valid N (listwise)			5294					5294					3889					826		
-2LL			1274.357					1141.614					698.976					191.138		
Omnibus χ^2/df/Sig.	.777		1		.378	133.520		5		.000	492.451		9		.000	228.804		11		.000
H-L χ^2/df/Sig.	103.524		8		.000	15.059		8		.058	10.350		8		.241	9.361		8		.313
Nagelkere R^2			.001					.117					.451					.607		

Table F-12 Logistic regression results for hypothesis 3, marine power

Variable	Model 1 B	Model 1 Sig.	Model 1 e^B	Model 1 95% CI for e^B Lower	Model 1 95% CI for e^B Upper	Model 2 B	Model 2 Sig.	Model 2 e^B	Model 2 95% CI for e^B Lower	Model 2 95% CI for e^B Upper	Model 3 B	Model 3 Sig.	Model 3 e^B	Model 3 95% CI for e^B Lower	Model 3 95% CI for e^B Upper	Model 4 B	Model 4 Sig.	Model 4 e^B	Model 4 95% CI for e^B Lower	Model 4 95% CI for e^B Lower
LEADER	.684	.091	1.981	.896	4.384	.864	.055	2.373	.981	5.741	-.593	.474	.553	.109	2.806	-1.180	.261	.307	.039	2.410
NON-LEADER	1.851	.000	6.364	4.454	9.092	1.450	.000	4.263	2.672	6.803	1.519	.000	4.569	2.526	8.264	.768	.036	2.155	1.050	4.422
NEIGHBOR						-.283	.186	.753	.495	1.146	-1.534	.000	.216	.120	.388	-1.571	.000	.208	.105	.411
STABLITY						.016	.000	1.016	1.012	1.021	-.019	.000	.981	.975	.988	-.029	.000	.971	.963	.980
REGIME						.001	.937	1.001	.968	1.036	-.160	.000	.852	.806	.901	-.126	.001	.882	.819	.950
TIME_LAG						.026	.001	1.026	1.011	1.042	.022	.043	1.022	1.001	1.045	.024	.096	1.025	.996	1.055
PATENTS											.589	.000	1.802	1.623	2.001	.615	.000	1.849	1.625	2.104
TRADE											-.004	.149	.996	.990	1.002	-.012	.040	.988	.977	.999
INVEST											.001	.992	1.001	.790	1.270	.586	.001	1.797	1.254	2.575
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																NA[a]	NA[a]	NA[a]	NA[a]	NA[a]
HUMAN_CAP																-.060	.002	.942	.907	.978
Intercept	-4.448	.000	.012			-5.464	.000	.004			-7.770	.000	.000			-9.657	.000	.000	.039	2.410
Valid N (listwise)			5368					5294					3889					2310		
-2LL			1168.355					1098.230					669.202					466.952		
Omnibus χ^2/df/Sig.	110.609		2	.000		176.904		6	.000		522.225		10	.000		423.502		11	.000	
H-L χ^2/df/Sig.	3.288		1	.070		28.401		8	.000		5.014		8	.756		7.497		8	.439	
Nagelkere R^2			.096					.154					.476					.524		

[a] the final solution could not be found when GOVS was included in the model

Table F-13 Logistic regression results for hypothesis 1, higher-speed rail

Variable	Model 1					Model 2					Model 3					Model 4				
	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.331	.000	1.393	1.358	1.429	.083	.000	1.086	1.048	1.126	.131	.000	1.140	1.082	1.201	.093	.008	1.097	1.024	1.175
NEIGHBOR						1.027	.000	2.792	2.454	3.176	1.118	.000	3.060	2.499	3.748	1.013	.000	2.755	2.058	3.688
STABLITY						.017	.000	1.018	1.015	1.021	-.012	.000	.988	.982	.993	.006	.180	1.006	.997	1.016
REGIME						.162	.000	1.176	1.135	1.219	-.005	.875	.995	.932	1.062	-.100	.075	.905	.810	1.010
TIME_LAG						.007	.195	1.007	.996	1.018	.039	.000	1.040	1.019	1.061	.004	.866	1.004	.962	1.048
PATENTS											.678	.000	1.971	1.792	2.166	.336	.000	1.399	1.229	1.591
TRADE											-.042	.000	.959	.950	.968	-.055	.000	.947	.935	.959
INVEST											.332	.002	1.393	1.134	1.712	.294	.136	1.342	.912	1.975
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																.075	.000	1.078	1.036	1.122
HUMAN_CAP																.071	.000	1.074	1.036	1.113
Intercept	-3.376	.000	.034			-5.397	.000	.005			-11.42	.000	.000			-13.10	.000	.000		
Valid N (listwise)			6784					6670					4812					998		
-2LL			2673.669					1782.057					803.971					390.784		
Omnibus χ^2/df/Sig.	621.678		1	.000		1492.343		5	.000		1985.216		9	.000		719.390		11	.000	
H-L χ^2/df/Sig.	55.401		1	.000		24.172		8	.002		4.835		8	.775		13.138		8	.107	
Nagelkere R^2			.228					.517					.768					.765		

Table F-14 Logistic regression results for hypothesis 2, higher-speed rail

Variable	Model 1 B	Model 1 Sig.	Model 1 e^B	Model 1 95% CI for e^B Lower	Model 1 95% CI for e^B Upper	Model 2 B	Model 2 Sig.	Model 2 e^B	Model 2 95% CI for e^B Lower	Model 2 95% CI for e^B Upper	Model 3 B	Model 3 Sig.	Model 3 e^B	Model 3 95% CI for e^B Lower	Model 3 95% CI for e^B Upper	Model 4 B	Model 4 Sig.	Model 4 e^B	Model 4 95% CI for e^B Lower	Model 4 95% CI for e^B Lower
DISSIMILARITY	-.025	.000	.975	.972	.979	.003	.330	1.003	.997	1.008	.002	.736	1.002	.993	1.011	.028	.014	1.028	1.006	1.051
NEIGHBOR						1.108	.000	3.027	2.670	3.431	1.079	.000	2.941	2.409	3.590	.918	.000	2.505	1.891	3.319
STABLITY						.018	.000	1.018	1.015	1.021	-.013	.000	.987	.981	.992	.002	.708	1.002	.993	1.011
REGIME						.208	.000	1.231	1.148	1.320	.049	.470	1.051	.919	1.201	.380	.052	1.463	.996	2.148
TIME_LAG						.012	.049	1.012	1.000	1.025	.044	.000	1.045	1.022	1.069	-.031	.250	.969	.919	1.022
PATENTS											.662	.000	1.938	1.765	2.129	.321	.000	1.378	1.212	1.566
TRADE											-.037	.000	.963	.955	.972	-.054	.000	.948	.936	.959
INVEST											.389	.000	1.476	1.209	1.801	.337	.086	1.401	.954	2.057
SURFACE											.000	.002	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																.063	.002	1.065	1.024	1.108
HUMAN_CAP																.086	.000	1.090	1.050	1.131
Intercept	-1.577	.000	.207			-5.831	.000	.003			-12.44	.000	.000			-17.56	.000	.000		
Valid N (listwise)			6670					6670					4812					998		
-2LL			2912.479					1801.677					828.161					391.183		
Omnibus χ^2/df/Sig.	361.921		1		.000	1472.723		5		.000	1961.026		9		.000	718.991		11		.000
H-L χ^2/df/Sig.	218.199		8		.000	17.395		8		.026	14.663		8		.066	9.984		8		.266
Nagelkere R^2			.136					.511					.761					.765		

Table F-15 Logistic regression results for hypothesis 3, higher-speed rail

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
LEADER	.228	.085	1.256	.969	1.628	.278	.120	1.321	.930	1.874	-.952	.001	.386	.222	.670	-.696	.203	.499	.171	1.457
NON-LEADER	2.672	.000	14.476	11.260	18.609	.915	.000	2.497	1.803	3.459	1.809	.000	6.104	3.734	9.979	2.046	.000	7.735	2.819	21.223
NEIGHBOR						.939	.000	2.557	2.241	2.919	.976	.000	2.653	2.166	3.248	1.024	.000	2.786	2.071	3.746
STABLITY						.018	.000	1.018	1.015	1.021	-.017	.000	.983	.977	.989	.009	.076	1.009	.999	1.019
REGIME						.152	.000	1.165	1.124	1.207	.029	.450	1.029	.955	1.109	-.113	.051	.893	.797	1.001
TIME_LAG						.018	.000	1.019	1.008	1.029	.056	.000	1.058	1.036	1.081	.027	.260	1.027	.980	1.076
PATENTS											.686	.000	1.986	1.802	2.188	.321	.000	1.378	1.206	1.574
TRADE											-.044	.000	.957	.948	.966	-.059	.000	.942	.929	.956
INVEST											.437	.000	1.548	1.251	1.916	.265	.215	1.303	.858	1.979
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																.070	.002	1.072	1.027	1.120
HUMAN_CAP																.083	.000	1.086	1.044	1.130
Intercept	-3.702	.000	.025			-5.948	.000	.003			-12.94	.000	.000			-14.29	.000	.000		
Valid N (listwise)			6784					6670					4812					998		
-2LL			2592.836					1741.476					768.809					370.651		
Omnibus χ^2/df/Sig.	702.510		2	.000		1532.924		6	.000		2020.378		10	.000		739.523		12	.000	
H-L χ^2/df/Sig.	27.489		1	.000		10.047		8	.262		7.245		8	.510		15.170		8	.056	
Nagelkere R^2			.256					.529					.779					.780		

Table F-16 Logistic regression results for hypothesis 1, high-speed rail

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.445	.000	1.560	1.490	1.633	.095	.003	1.100	1.033	1.171	.183	.000	1.200	1.087	1.325	.202	.001	1.224	1.089	1.374
NEIGHBOR						1.027	.000	2.793	2.335	3.342	1.286	.000	3.618	2.607	5.021	.721	.000	2.056	1.431	2.953
STABLITY						-.003	.160	.997	.993	1.001	-.034	.000	.967	.959	.974	-.023	.000	.977	.967	.988
REGIME						.287	.000	1.333	1.234	1.440	-.056	.209	.946	.866	1.032	-.158	.007	.854	.761	.957
TIME_LAG						.018	.020	1.018	1.003	1.034	.050	.002	1.051	1.019	1.085	.053	.059	1.055	.998	1.115
PATENTS											.760	.000	2.137	1.895	2.411	.501	.000	1.651	1.392	1.957
TRADE											-.037	.000	.963	.953	.974	-.030	.000	.971	.958	.983
INVEST											.319	.036	1.376	1.022	1.852	.471	.043	1.601	1.015	2.525
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	.999	1.000
GOV_SIZE																-.081	.000	.922	.882	.964
HUMAN_CAP																.016	.496	1.016	.971	1.062
Intercept	-3.964	.000	.019			-6.323	.000	.002			-12.11	.000	.000			-10.61	.000	.000		
Valid N (listwise)			6784					6670					4812					998		
-2LL			1630.094					1229.336					508.646					329.720		
Omnibus χ^2/df/Sig.	290.901		1	.000		684.183		5	.000		1167.675		9	.000		345.971		11	.000	
H-L χ^2/df/Sig.	.000[a]		0	.		35.671		8	.000		13.939		8	.083		10.177		8	.253	
Nagelkere R^2			.170					.391					.732					.596		

[a] the model is saturated

Table F-17 Logistic regression results for hypothesis 2, high-speed rail

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
DISSIMILARITY	-.016	.000	.984	.979	.990	.026	.000	1.026	1.016	1.036	.023	.004	1.024	1.008	1.040	.014	.212	1.014	.992	1.036
NEIGHBOR						1.093	.000	2.982	2.505	3.551	1.164	.000	3.202	2.340	4.382	.713	.000	2.040	1.437	2.895
STABLITY						-.004	.054	.996	.991	1.000	-.033	.000	.967	.960	.975	-.024	.000	.976	.966	.986
REGIME						.509	.000	1.663	1.474	1.876	.225	.019	1.253	1.037	1.513	.037	.770	1.037	.811	1.326
TIME_LAG						.002	.851	1.002	.985	1.018	.039	.023	1.040	1.005	1.075	.039	.315	1.040	.964	1.121
PATENTS											.718	.000	2.051	1.822	2.309	.473	.000	1.604	1.365	1.886
TRADE											-.034	.000	.966	.956	.977	-.030	.000	.971	.959	.983
INVEST											.441	.003	1.555	1.165	2.076	.486	.024	1.625	1.065	2.480
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	1.000	1.000
GOV_SIZE																-.066	.002	.936	.898	.975
HUMAN_CAP																.028	.189	1.028	.986	1.071
Intercept	-2.981	.000	.051			-7.948	.000	.000			-15.62	.000	.000			-12.74	.000	.000		
Valid N (listwise)			6670					6670					4812					998		
-2LL			1868.761					1213.832					513.261					340.920		
Omnibus χ^2/df/Sig.	44.759		1		.000	699.688		5		.000	1163.061		9		.000	334.771		11		.000
H-L χ^2/df/Sig.	174.422		8		.000	19.250		8		.014	6.304		8		.613	1.523		8		.992
Nagelkere R^2			.027					.399					.730					.579		

Table F-18 Logistic regression results for hypothesis 3, high-speed rail

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
LEADER	-.529	.233	.589	.246	1.407	.443	.384	1.558	.575	4.220	2.327	.001	10.242	2.524	41.562	1.251	.187	3.494	.544	22.449
NON-LEADER	2.988	.000	19.855	14.836	26.573	1.010	.000	2.745	1.951	3.862	1.862	.000	6.435	3.520	11.765	3.007	.000	20.220	7.435	54.993
NEIGHBOR						.926	.000	2.525	2.113	3.017	1.092	.000	2.980	2.096	4.238	.683	.002	1.980	1.292	3.034
STABLITY						-.002	.309	.998	.994	1.002	-.034	.000	.967	.959	.975	-.019	.002	.981	.969	.993
REGIME						.270	.000	1.310	1.214	1.414	-.059	.222	.943	.859	1.036	-.098	.201	.907	.781	1.053
TIME_LAG						.020	.007	1.020	1.005	1.036	.061	.000	1.063	1.030	1.097	.099	.001	1.104	1.039	1.174
PATENTS											.869	.000	2.384	2.073	2.741	.542	.000	1.719	1.409	2.097
TRADE											-.035	.000	.965	.955	.976	-.026	.000	.975	.962	.988
INVEST											.197	.203	1.217	.899	1.649	.494	.055	1.639	.989	2.719
SURFACE											.000	.000	1.000	1.000	1.000	.000	.000	1.000	.999	1.000
GOV_SIZE																-.100	.000	.905	.860	.952
HUMAN_CAP																-.018	.501	.982	.933	1.035
Intercept	-4.318	.000	.013			-6.474	.000	.002			-12.37	.000	.000			-12.15	.000	.000		
Valid N (listwise)			6784					6670					4812					998		
-2LL			1529.496					1203.665					471.726					286.446		
Omnibus χ^2/df/Sig.	391.500		2		.000	709.855		6		.000	1204.596		10		.000	389.245		12		.000
H-L χ^2/df/Sig.	.617		1		.432	27.859		8		.001	9.198		8		.326	20.917		8		.007
Nagelkere R^2			.227					.405					.753					.657		

Table F-19 Logistic regression results for hypothesis 1, telecommunication satellites

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.259	.000	1.296	1.279	1.313	.168	.000	1.183	1.166	1.200	.182	.000	1.200	1.174	1.226	.064	.002	1.066	1.025	1.110
NEIGHBOR						1.016	.000	2.763	2.528	3.019	.926	.000	2.524	2.220	2.868	1.250	.000	3.489	2.575	4.727
STABLITY						.034	.000	1.035	1.032	1.038	.013	.000	1.013	1.009	1.018	.033	.000	1.033	1.019	1.048
REGIME						.028	.000	1.028	1.015	1.042	-.135	.000	.873	.852	.895	-.246	.000	.782	.736	.831
TIME_LAG						.033	.000	1.034	1.025	1.042	.066	.000	1.068	1.054	1.082	.027	.143	1.027	.991	1.065
PATENTS											.523	.000	1.687	1.584	1.797	.363	.000	1.438	1.259	1.642
TRADE											.003	.056	1.003	1.000	1.005	.003	.454	1.003	.996	1.009
INVEST											-.041	.444	.960	.863	1.067	.580	.000	1.786	1.355	2.353
SURFACE											.000	.000	1.000	1.000	1.000	.002	.000	1.002	1.001	1.002
GOV_SIZE																-.011	.622	.989	.948	1.033
HUMAN_CAP																-.029	.079	.971	.940	1.003
Intercept	-2.481	.000	.084			-5.485	.000	.004			-8.027	.000	.000			-11.04	.000	.000		
Valid N (listwise)			7218					7098					4812					998		
-2LL			4855.522					3156.771					1840.524					449.587		
Omnibus χ^2/df/Sig.	2596.214		1		.000	4143.119		5		.000	3655.408		9		.000	933.678		11		.000
H-L χ^2/df/Sig.	49.637		3		.000	30.555		8		.000	18.551		8		.017	10.025		8		.263
Nagelkere R^2			.469					.688					.782					.810		

Table F-20 Logistic regression results for hypothesis 2, telecommunication satellites

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
DISSIMILARITY	.006	.000	1.006	1.005	1.006	.003	.000	1.003	1.002	1.004	.003	.000	1.003	1.002	1.005	.005	.007	1.005	1.001	1.008
NEIGHBOR						1.239	.000	3.452	3.178	3.749	1.224	.000	3.399	3.031	3.812	1.289	.000	3.630	2.677	4.923
STABLITY						.033	.000	1.034	1.031	1.037	.007	.003	1.007	1.002	1.011	.025	.000	1.025	1.011	1.040
REGIME						.035	.000	1.036	1.020	1.051	-.103	.000	.902	.880	.925	-.214	.000	.807	.758	.861
TIME_LAG						.024	.000	1.024	1.013	1.036	.028	.001	1.028	1.011	1.045	-.004	.840	.996	.954	1.039
PATENTS											.357	.000	1.429	1.357	1.505	.405	.000	1.500	1.304	1.725
TRADE											.002	.100	1.002	1.000	1.005	.003	.407	1.003	.996	1.009
INVEST											.301	.000	1.351	1.239	1.472	.575	.000	1.777	1.358	2.326
SURFACE											.000	.000	1.000	1.000	1.000	.002	.000	1.002	1.001	1.002
GOV_SIZE																.002	.929	1.002	.961	1.044
HUMAN_CAP																-.032	.045	.968	.939	.999
Intercept	-2.994	.000	.050			-5.417	.000	.004			-10.33	.000	.000			-11.09	.000	.000		
Valid N (listwise)			7098					7098					4812					998		
-2LL			6300.604					3733.437					2119.647					452.061		
Omnibus χ^2/df/Sig.	999.286		1	.000		3566.453		5	.000		3376.284		9	.000		931.204		11	.000	
H-L χ^2/df/Sig.	206.284		8	.000		44.599		8	.000		27.703		8	.001		16.977		8	.030	
Nagelkere R^2			.204					.615					.741					.809		

Table F-21 Logistic regression results for hypothesis 3, telecommunication satellites

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
LEADER	.560	.000	1.751	1.506	2.034	.678	.000	1.969	1.565	2.478	-.092	.595	.912	.649	1.281	-.243	.641	.784	.282	2.180
NON-LEADER	1.879	.000	6.548	5.675	7.556	.708	.000	2.030	1.621	2.542	1.294	.000	3.647	2.622	5.073	-.045	.927	.956	.362	2.526
NEIGHBOR						1.199	.000	3.317	3.046	3.611	1.150	.000	3.158	2.808	3.551	1.423	.000	4.149	3.044	5.655
STABLITY						.035	.000	1.036	1.033	1.039	.012	.000	1.012	1.007	1.017	.027	.000	1.028	1.014	1.042
REGIME						.003	.648	1.003	.991	1.015	-.157	.000	.855	.835	.875	-.254	.000	.776	.731	.823
TIME_LAG						.043	.000	1.044	1.035	1.052	.058	.000	1.060	1.048	1.073	.030	.107	1.030	.994	1.068
PATENTS											.425	.000	1.530	1.445	1.621	.375	.000	1.455	1.269	1.670
TRADE											.003	.035	1.003	1.000	1.006	.001	.660	1.001	.995	1.008
INVEST											.203	.000	1.225	1.114	1.347	.589	.000	1.803	1.373	2.367
SURFACE											.000	.000	1.000	1.000	1.000	.002	.000	1.002	1.001	1.002
GOV_SIZE																-.003	.899	.997	.958	1.038
HUMAN_CAP																-.025	.121	.975	.944	1.007
Intercept	-2.537	.000	.079			-5.959	.000	.003			-10.02	.000	.000			-10.98	.000	.000		
Valid N (listwise)			7218					7098					4812					998		
-2LL			6166.255					3572.097					2060.441					458.830		
Omnibus χ^2/df/Sig.	1285.480		2		.000	3727.793		6		.000	3435.491		10		.000	924.435		12		.000
H-L χ^2/df/Sig.	96.764		2		.000	19.093		8		.014	31.351		8		.000	16.565		8		.035
Nagelkere R^2			.253					.636					.749					.805		

Table F-22 Logistic regression results for hypothesis 1, meteorological satellites

Variable	Model 1					Model 2					Model 3					Model 4				
	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
ALLY	.297	.000	1.346	1.322	1.371	.063	.000	1.065	1.032	1.099	.102	.000	1.107	1.064	1.152	.030	.337	1.031	.969	1.097
NEIGHBOR						1.838	.000	6.287	5.278	7.488	1.570	.000	4.806	3.873	5.963	1.221	.000	3.391	2.286	5.031
STABLITY						.039	.000	1.040	1.035	1.044	.021	.000	1.021	1.015	1.028	.057	.000	1.058	1.037	1.080
REGIME						.097	.000	1.101	1.074	1.129	.126	.000	1.134	1.065	1.209	.744	.001	2.104	1.346	3.289
TIME_LAG						.012	.030	1.013	1.001	1.024	.049	.000	1.051	1.032	1.070	.081	.005	1.085	1.025	1.148
PATENTS											.508	.000	1.661	1.534	1.800	.264	.003	1.302	1.092	1.552
TRADE											-.004	.054	.996	.991	1.000	-.020	.000	.980	.971	.988
INVEST											-.280	.002	.756	.634	.900	.462	.021	1.587	1.071	2.352
SURFACE											.000	.502	1.000	1.000	1.000	.000	.083	1.000	1.000	1.000
GOV_SIZE																-.047	.066	.954	.907	1.003
HUMAN_CAP																-.074	.001	.928	.888	.971
Intercept	-3.147	.000	.043			-6.565	.000	.001			-7.023	.000	.001			-13.62	.000	.000		
Valid N (listwise)			7218					7098					4812					998		
-2LL			3308.479					1414.817					873.224					313.468		
Omnibus χ^2/df/Sig.	1088.410		1	.000		2954.433		5	.000		2711.738		9	.000		957.476		11	.000	
H-L χ^2/df/Sig.	6.755		2	.034		24.369		8	.002		3.303		8	.914		6.797		8	.559	
Nagelkere R^2			.307					.741					.820					.857		

Table F-23 Logistic regression results for hypothesis 2, meteorological satellites

	Model 1					Model 2					Model 3					Model 4				
Variable	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
DISSIMILARITY	-.011	.000	.989	.988	.991	-.008	.000	.992	.990	.995	-.003	.561	.997	.989	1.006	-.062	.000	.940	.908	.973
NEIGHBOR						2.030	.000	7.614	6.375	9.092	1.727	.000	5.623	4.521	6.994	1.235	.000	3.438	2.343	5.044
STABLITY						.040	.000	1.041	1.037	1.046	.018	.000	1.018	1.011	1.024	.053	.000	1.055	1.035	1.074
REGIME						.016	.397	1.016	.979	1.054	.112	.160	1.118	.957	1.307	-.089	.616	.915	.647	1.294
TIME_LAG						.035	.000	1.036	1.022	1.049	.058	.000	1.059	1.040	1.080	.129	.000	1.137	1.067	1.212
PATENTS											.481	.000	1.617	1.495	1.749	.328	.000	1.388	1.162	1.658
TRADE											-.003	.161	.997	.993	1.001	-.019	.000	.981	.972	.989
INVEST											-.188	.030	.829	.699	.982	.428	.035	1.533	1.031	2.280
SURFACE											.000	.834	1.000	1.000	1.000	.000	.046	1.000	1.000	1.000
GOV_SIZE																-.045	.079	.956	.909	1.005
HUMAN_CAP																-.072	.002	.930	.889	.974
Intercept	-1.620	.000	.198			-6.348	.000	.002			-7.713	.000	.000			-5.834	.006	.003		
Valid N (listwise)			7098					7098					4812					998		
-2LL			4026.568					1398.427					898.451					307.107		
Omnibus χ^2/df/Sig.	342.681		1		.000	2970.822		5		.000	2686.511		9		.000	963.837		11		.000
H-L χ^2/df/Sig.	334.240		7		.000	19.681		8		.012	6.323		8		.611	10.742		8		.217
Nagelkere R^2			.103					.744					.814					.860		

Table F-24 Logistic regression results for hypothesis 3, meteorological satellites

Variable	Model 1					Model 2					Model 3					Model 4				
	B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B		B	Sig.	e^B	95% CI for e^B	
				Lower	Upper				Lower	Upper				Lower	Upper				Lower	Lower
LEADER	-.249	.024	.779	.628	.968	-.639	.001	.528	.365	.763	-2.122	.000	.120	.065	.221	-2.983	.000	.051	.011	.225
NON-LEADER	2.419	.000	11.231	9.065	13.915	1.007	.000	2.737	1.873	4.000	2.531	.000	12.570	6.907	22.877	2.498	.001	12.160	2.791	52.987
NEIGHBOR						1.824	.000	6.196	5.229	7.341	1.488	.000	4.429	3.560	5.509	1.269	.000	3.558	2.406	5.263
STABLITY						.038	.000	1.039	1.035	1.043	.014	.000	1.014	1.007	1.022	.058	.000	1.060	1.038	1.082
REGIME						.120	.000	1.127	1.099	1.156	.245	.000	1.277	1.169	1.395	.775	.001	2.170	1.400	3.364
TIME_LAG						.010	.097	1.010	.998	1.021	.045	.000	1.046	1.025	1.066	.047	.127	1.048	.987	1.114
PATENTS											.616	.000	1.851	1.684	2.035	.337	.000	1.400	1.168	1.679
TRADE											-.005	.041	.995	.991	1.000	-.022	.000	.978	.969	.987
INVEST											-.257	.012	.773	.632	.945	.459	.030	1.582	1.044	2.396
SURFACE											.000	.104	1.000	1.000	1.000	.000	.095	1.000	1.000	1.000
GOV_SIZE																-.057	.029	.945	.898	.994
HUMAN_CAP																-.066	.007	.936	.892	.982
Intercept	-3.076	.000	.046			-6.391	.000	.002			-7.904	.000	.000			-12.50	.000	.000		
Valid N (listwise)			7218					7098					4812					998		
-2LL			3702.155					1402.214					812.604					299.412		
Omnibus χ^2/df/Sig.	694.734		2	.000		2967.036		6	.000		2772.357		10	.000		971.532		12	.000	
H-L χ^2/df/Sig.	.013		1	.909		20.588		8	.008		21.384		8	.006		54.340		8	.000	
Nagelkere R^2			.201					.743					.834					.864		

Appendix G. Assumptions of logistic regression

The assumptions behind the logistic regression model are (Salkind, 2010):

- The independent variables are linearly and additively correlated to $logit(Y)$,
- Each case is independent from the other cases is the sample,
- Variables are measured without error,
- All relevant independent variables have been included,
- No irrelevant independent variables have been included,
- No independent variable is perfectly colinear with one or more independent variables. Collinearity occurs when independent variables provide redundant information.

The assumptions impose some limitations to using LR:

- Model validity depends on the number and suitability of the selected independent variables (Tolles & Meurer, 2016),
- All independent variables must have a constant magnitude of association for the whole value range they take (Tolles & Meurer, 2016),
- When interaction (the values of independent variables influence each other) between independent variables occurs, it must be explicitly included in the model (Tolles & Meurer, 2016).