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Essays on the Endogenous Dynamics of Technological Diversity

: the Case of Photovoltaic Technology in Evolutionary Economics

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: the Case of Photovoltaic Technology in Evolutionary Economics

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In heartfelt dedication to my children,

Yisol & Yiheon,

who are the center of my universe

Abstract

Essays on the Endogenous Dynamics of Technological Diversity

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Technological diversity is both a stimulus and an indicator of innovation. It arises from the recombination of technologies, which leads to the creation of more diversified and differentiated technologies. Diversity in technology fluctuates over the course of an economic development. The dynamics of technological diversity provide insights into the growth stages of technologies and industries, and guide government policies and business strategies. However, our empirical understanding of technological diversity remains

limited. Previous studies have measured technological diversity at the level of broad categories of technologies, such as industries, without considering technological trajectories. In addition, there is a lack of explanation for the endogenous mechanisms that generate and change technological diversity.

In order to efficiently and effectively promote technological diversity as a source of innovation, it is crucial to fill these knowledge gaps. This study aims to quantify technological diversity by considering detailed trajectories and to understand the endogenous mechanisms of its dynamics. To this end, the study adopts an evolutionary perspective and takes evolutionary economics as its theoretical foundation. This study employs an evolutionary phylogenetic approach to quantify technological diversity, incorporating information from technological evolutionary processes and specific trajectories. The evolutionary phylogenetic tree of technology is used as a key analytical framework throughout the study. It also highlights technological search and organizational routines as factors to derive a generalized framework for the endogenous dynamics of technological diversity. The empirical analysis is carried out in the field of photovoltaic technology.

Chapter 4 explores the quantification of technological diversity by considering detailed trajectories in the process of technological evolution. The analysis in this chapter uses 8,081 photovoltaic technology patents granted by the U.S. Patent and Trademark Office (USPTO) from 2000 to 2018. After constructing an evolutionary phylogenetic tree for photovoltaic technology, technological diversity of the specific trajectories is measured by the entropy for the information derived from the phylogenetic tree. The results of this chapter are used for further analysis in Chapter 5 and 6. The evolutionary phylogenetic tree of photovoltaic technology derived from this analysis provides a robust description of the actual history. While technological diversity has increased gradually overall, each of the trajectories have seen a more radical change. The analysis shows that technological diversity has stagnated or declined since 2015 in terms of both aggregate and trajectory-specific diversity measures, suggesting a weakening innovation momentum in photovoltaic technology.

Chapter 5 examines the dynamics of technological dynamics for technological search, in terms of considering the nature of the technology itself. Technological search is classified into three patterns, analogous to biological evolution: Vertical Inheritance (VI), Horizontal Gene Transfer (HGT), and Mutation (MT). In this chapter, the relationship between diversity dynamics and technological search is derived through regression analysis. The empirical results indicate that the VI pattern of technological search is dominant in the evolution of photovoltaic technology, while HGT occurs the least frequently. Both VI and HGT search patterns have a statistically significant relationship with technological diversity, either decreasing or increasing it. However, the MT search pattern is not significantly related to diversity. In addition, these relationships are not found to be differentially affected by time period. Therefore, the findings in this chapter highlight technological search as a driver of diversity dynamics, with recombining technologies from neighboring ancestors identified in an evolutionary phylogenetic tree playing a crucial role in increasing technological diversity.

Chapter 6 discusses the relationship between organizational routines and diversity dynamics from the perspective of actors in technological development. The analysis consists of two parts: i) identifying and categorizing organizational innovation routines, and ii) examining the relationship between routines and diversity dynamics. Innovation routines are identified through multidimensional firm behaviors, and then categorized into four types through relative comparison within the sector: Active Pioneer (AP), Efficient Optimizer (EO), Passive Observer (PO), and Adoptive Adventurer (AA). The study uses granted patent data from the USPTO and photovoltaic module data from PVsyst version 6.0 for the period 2000-2022. The relationship between innovation routines and diversity dynamics is examined using regression analysis.

The results in this chapter confirm that the method of quantifying and classifying innovation routines is valid for identifying inherent characteristics of firms. The regression results indicate that organizational routines are endogenous factors influencing technological diversity. The AA type shows a significant positive relationship with technological diversity, especially when combined with the HGT search pattern. Furthermore, the impact of technological search on diversity dynamics derived in Chapter 5 depends on organizational routines.

In conclusion, technological search drives the dynamics of technological diversity, and based on this, the principle of generating technological diversity is the gradual expansion of technological space through recombination with other relevant technologies. Organizational routines act as micro-criteria for the dynamics of technological diversity by

determining a firm's technological search behavior (i.e., the manner, scope, and extent of technological search). This study introduces technological search and organizational routines as new factors to explain the endogenous dynamics of technological diversity, thereby enhancing the explanatory power of technological diversity dynamics from an evolutionary perspective.

The application of evolutionary phylogenetic methodology complements the limitations of previous comprehensive studies and contributes to a deeper understanding of dynamic processes in technological development. Furthermore, these findings have practical implications for business strategies and government policies aimed at promoting technological innovation. The empirical analysis of photovoltaic technology provides a scientific basis for practical suggestions to address industry challenges.

Keywords: Evolutionary Economics; Technology Evolution; Diversity Dynamics; Technological Search; Organizational Routine; Photovoltaics

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Glossary of Terms

CH.	Terms (Abbreviation)	Definitions in This Study
4	**Technological Diversity**	The state of being different or varied within a specific technological regime
	Technology Space	The space in which technologies develop, resulting in a set of technology trajectories. In evolutionary perspectives, it represents the fitness landscape for technology evolution
	Evolutionary Phylogenetic Tree	The network that consists of taxa with genetic homogeneity as nodes, and evolutionary relationships between taxa as links
5	**Technological Search**	The activity for innovation to seek either new technologies or the new combination of existing technologies (or technology elements). It is specified into three patterns in this study, such as vertical inheritance, horizontal gene transfer, and mutation.
	Vertical Inheritance (VI)	One of the patterns in technological search. Descendant technology inherits and deepens the technological elements of direct ancestor, and it represents incremental innovation within the trajectory of existing technologies
	Horizontal Gene Transfer (HGT)	One of the patterns in technological search. Descendant technology receives new technological elements from a neighbor ancestor, and it represents combinatorial innovation with new, but related technology

	Mutation (MT)	One of the patterns in technological search. Descendant technology receives new technological elements that are not observed in previous generations. If successful, it represents radical innovation, but it also has high risk to fail due to difficulty of adaptation
6	**Organizational Routine**	Recurrent behavioral patterns of organization. It is the inherent and static characteristic of a firm and determines a firm's behaviors
	Sectoral Regime	Technological and industrial environment surrounding the firm. It is a set of specific technological paradigms, which refers to the sectoral specificity of patterns on technological development and the characteristics of innovation actor
	Innovation Routine	Recurrent behavioral patterns of organization to realize new technological combinations
	Innovation Behavior	Organizational behavior to realize new technological combinations, consisting of *Knowing* and *Doing*
	Willingness for Novelty	Firm's disposition or desire to innovate based on Schumpeter's definition, that is the realization of a new combination
	Knowing	Firm's behavior for what to know, such as an innovation through technology R&D
	Doing	Firm's behavior for what to do, such as an implementation

	through the production
Exploration / Explorative	Indicator of a firm's willingness to novelty. Firms with a strong willingness for novelty and whose innovation behavior stays within a new and unfamiliar space are more likely to have an explorative innovation routine
Exploitation / Exploitative	Indicator of a firm's willingness for novelty. Firms with a weak willingness for novelty and whose innovation behavior stays within an experienced and familiar space are more likely to have an exploitative innovation routine
Active Pioneer (AP)	One of the types of innovation routines categorized in this study. It is explorative in both *Knowing* and *Doing*
Efficient Optimizer (EO)	One of the types of innovation routines categorized in this study. It is exploitative in *Knowing*, while explorative in *Doing*
Passive Observer (PO)	One of the types of innovation routines categorized in this study. It is exploitative in both *Knowing* and *Doing*
Adoptive Adventurer (AA)	One of the types of innovation routines categorized in this study. It is explorative in *Knowing*, while exploitative in *Doing*

Chapter 1. Introduction

1.1 Background and Motivation

Different technologies give rise to various technologies in turn. Innovation is an endogenous process (Fleming, 2001; Schumpeter, 1942) that is "created by a substantial extent of recombination of conceptual and physical materials that were previously in existence (Nelson & Winter, 1982: 130)." Current technological advances have emerged from the nourishment of previously accumulated diverse knowledge and technologies. The examples are endless. The smartphone is the result of the recombination of telecommunication technologies accumulated from mobile phones, with cameras, touch screens, and various technologies in the IT field. Siri, Google Assistant, chat bot, and language translation systems are the result of the development of deep learning algorithms such as Recurrent Neural Networks (RNN) and Natural Language Processing (NLP) technology. The seeds of innovation lie in technological diversity.

The concept of diversity becomes even more important when viewed through the lens of evolution. Diversity is a driving force in evolution, affecting both selection and variation. In addition, selection mechanisms produce better results with greater diversity (Fisher, 1930; Metcalfe, 1994, 1998)[1].

This study examines technological diversity within the theoretical framework of

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[1] Ronald A. Fisher's work, "The Genetic Theory of Natural Selection (1930)," which played a pivotal role in reformulating the theory of natural selection into a mathematical model based on genetics, showed that the more the genetic variability over which fitness selection acts, the greater the expected improvement in fitness.

evolutionary economics. From this perspective, technological diversity plays an important role in the dynamics of economic development (Dopfer, 2001; Frenken et al., 1999). Economies adapt and develop through the exploration and diversification of technological options. Technological diversity creates opportunities for experimentation, learning, and the emergence of new capabilities, and enhances adaptability and survivability in uncertain, complex, and rapidly changing environments (Kauffman & Weinberger, 1989; Levinthal, 1998). Competition among different technologies leads to evolution toward new technological designs (Anderson & Tushman, 1990; Utterback & Abernathy, 1975) and creates niches that provide opportunities for innovation (Frenken et al., 1999). Moreover, maintaining technological diversity reduces dependence on a particular dominant technology and increases systemic flexibility, opening up possibilities for further innovation (Carroll & Hannan, 2018; Stirling, 2010).

Certainly, “there are no free lunches for diversity (Weitzman, 1992: 363).” Higher levels of technological diversity may be associated with higher costs. This is because, in terms of short-term efficiency or net present value optimization, technology standardization and specialization are more economically feasible. The lower the level of technological diversity, the higher the freedom from coordination and compatibility problems and the greater the returns to scale that can be enjoyed through more market share (Lacerda & Van Den Bergh, 2016; Van Den Bergh, 2008). In addition, a high level of technological diversity has economic constraints in terms of resource allocation and concentration or learning effects according to path dependence.

Should we still strive for technological diversity? Standing on the shoulders of giants in evolutionary economics as mentioned above, the answer of this study is *yes*. The tapestry of technological progress is a mosaic of diverse technologies, each providing its own thread in the fabric of progress. As observed in film photography technology, home audio technology, or mobile operating system technology, the decline of technological diversity leads to industry decline or stagnation of innovation. Therefore, technological diversity is essential for long-term economic growth and innovation.

From the perspective of evolutionary economics, technological development is described as a process of evolutionary change in technology based on the generation of technological diversity and competitive selection (Cohendet et al., 1992). In this process, technological diversity fluctuates constantly, increasing, decreasing, and sometimes stagnating during economic development. The emergence of an industry attracts many innovators and ideas, thereby increasing technological diversity. On the other hand, competition among different technologies leads to the emergence of dominant designs that are selected by the market, causing diversity to stagnate or decline (Anderson & Tushman, 1990; Utterback & Abernathy, 1975). Technological diversity creates and modifies technological trajectories through dynamic changes, guiding the direction of innovation and enhancing the rate of innovation (Grandstand, 1998; Kim & Kogut, 1996; Quintana-García & Benavides-Velasco, 2008; Suzuki and Kodama, 2004). The dynamics of technological diversity serve as an indicator of the developmental stage of a technology or industry and a basis for innovation activities (Gao et al., 2013; Lin et al., 2021; Pavitt, 1998).

Based on information about technological diversity and its dynamics, governments set industrial policies and firms make decisions about strategic actions (Suarez & Utterback, 1995; Utterback & Abernathy, 1975). Given the theoretical and practical importance of technological diversity and its dynamics, many scholars have attempted to gain a better understanding of it; however, the empirical understanding of the dynamics of technological diversity remains limited (Frenken et al., 1999).

1.2 Objectives and Scope

The academic gaps that have been identified in the literature can be divided into two main areas.

First, there are gaps in the existing literature on quantitative measures of technological diversity. Scholars have measured diversity at the level of broad categories of technology, such as industries (e.g., Utterback & Abernathy, 1975). However, technologies evolve in a space with more than one technological trajectory. Technological diversity measured at the aggregate level may differ from the outcome along detailed technological trajectories, and thus quantifying technological diversity at the broad level may be subject to errors of generalization.

The second is the lack of clarity on the endogenous mechanisms of technological diversity dynamics. In previous works, the emergence and variation of technological diversity have mainly relied on intuitive and conceptual explanations based on researchers' insights. While external factors such as consensus on technology concepts (Grodal et al., 2015; Suarez et al., 2015), intra-industry competition (Anderson & Tushman, 1990), and increasing demand heterogeneity (Adner & Levinthal, 2001) are recognized as the main sources of technological diversity, the endogenous factors and processes that generate and change technological diversity have not been fully explained. Technological progress and innovation are endogenous (Fleming, 2001; Schumpeter, 1942). Therefore, understanding the endogenous mechanisms of the dynamics in technological diversity leads to an insight into the innovation process, where recombination between technologies creates novelty.

How does technological diversity, as a source and indicator of innovation, emerge and change? Answering these questions, and more importantly, uncovering the principles of technological diversity growth, will allow for more direct and practical innovation policies and strategies. Therefore, this study aims to understand the dynamics of technological diversity, that is the endogenous mechanisms of increment, stagnation, and decline. To this end, evolutionary perspectives and approaches are actively adopted to fill the academic gap in previous studies.

Specifically, this study applies an evolutionary phylogenetic methodology to the quantification of technological diversity, adding a spatial concept. An evolutionary phylogenetic tree is a network that represents evolutionary relationships based on genetic homogeneity and schematizes the different patterns that occur during evolution (Huson & Bryant, 2006). Evolutionary phylogenetic trees provide a holistic view of the evolutionary process on technology and allow the identification of specific trajectories of technological development. This study quantifies technological diversity based on information from phylogenetic trees to observe how diversity varies across technological trajectories formed during the evolution of technology.

Technological search and organizational routines are proposed as internal factors leading to the dynamics of technological diversity. This approach is grounded in perspectives of technological innovation models that focus either on the nature of the technology itself or the actors (Ma & Nakamori, 2005). Using evolutionary concepts from biology, this study defines technological search and organizational routines, respectively, and presents them as new measures to explain the endogenous dynamics of technological diversity.

The empirical analysis is conducted on photovoltaic technology. While the endogenous mechanism for technological diversity dynamics proposed in this study can be broadly applied to a variety of technologies and industries in general, photovoltaic technology is taken as an empirical case based on three rationales.

The first is the technological importance. Photovoltaic power generation is essential to a global energy portfolio. Over the past two decades, the photovoltaic industry has grown rapidly, and technological advances have been at the heart of this growth. Given the key role of photovoltaics in sustainability, it is therefore important to understand the current state and future direction of the technology for innovation.

Second, the photovoltaic industry has been dynamic relative to the short time frame. Photovoltaic technology has been rapidly industrialized since 2000, experiencing remarkable growth and fierce competition. Currently, the industry is on a transition path from maturity to either decline or regeneration. The ability to observe most of the industry's life cycle over a comparatively short period of about 20 years is an advantage in terms of data availability. Furthermore, based on the industry life cycle theory, which uses the increase and decrease of diversity as an explanatory measure (Abernathy & Utterback, 1978Klepper & Graddy, 1990; Klepper & Simons, 2005; Markard, 2020), the dynamics of the photovoltaic industry are representative and appropriate to explain technological diversity.

Finally, photovoltaic technologies are divided into three generations based on their degree of commercialization. These commonly used generational classifications of technologies facilitate comparisons between technologies and understanding the chronological progression of technological advances.

The continuous introduction and development of different technologies is crucial for innovation (Dopfer, 2001; Frenken et al., 1999). This study explores the dynamic mechanism of technological diversity by focusing on technological search and organizational routines as internal factors and deriving their relationships in the space of technological evolution. The academic significance of this study is that first, it uses an evolutionary phylogenetic approach as a novel methodology to identify the specific trajectories and explain the phenomenon of technological development, and second, it proposes technological search and organizational routines as new metrics to understand the dynamics of technological diversity. While previous studies have focused primarily on exogenous factors, this study contributes to the broader discussion of technological evolution by shedding light on endogenous mechanisms. The results of the study contribute to improving the effectiveness and efficiency of innovation promotion strategies and policies. Specifically, it paves the way for evidence-based policy interventions and serves as a scientific basis for technology decision-making. Furthermore, the evolution of photovoltaic technology derived from the empirical analysis will directly suggest the direction of innovation and provide practical implications applicable to other industries with similar characteristics and challenges.

1.3 Outline of the Study

This study is organized as shown in **Figure 1-1**.

Chapter 2 reviews the existing literature on diversity, technological search, and organizational routines from the theory of evolution and evolutionary economics. It also introduces the evolutionary phylogenetic methodology for constructing the evolutionary space and trajectories of technologies. Based on the theoretical and methodological background, the conceptual framework of diversity dynamics developed in this study is presented.

Chapter 3 provides an overview of photovoltaics to set the groundwork for the empirical analysis. It first presents the rationale for selecting photovoltaic technology as the subject of the empirical analysis, followed by an overview of photovoltaic technology and historical facts about the industry and markets related to the technology.

Chapter 4 examines the dynamics of technological diversity using evolutionary phylogenetic methodology. The significance of this chapter is that it quantifies technological diversity along specific trajectories. The phylogenetic tree and the measured technological diversity obtained in this chapter are further used in Chapters 5 and 6.

Chapter 5 presents the patterns of technological search for diversity dynamics. Using the concept of evolution in biology, technological search is specified into three patterns, vertical inheritance (VI), horizontal gene transfer (HGT), and mutation (MT), and measured quantitatively through modeling. The patterns of technological search proposed in this chapter are distinctive in that they enhance the explanatory power of the scope, direction, and path dependence of technological search by reflecting the nature of the technology. The relationship between each search pattern and diversity dynamics is derived through regression analysis.

Chapter 6 consists of two parts. The first takes a multidimensional approach to firm behavior to derive organizational routines. To identify and classify innovation routines for firms, this study measures firms' willingness for novelty in terms of their *Knowing* and *Doing* behaviors. Innovation routines are derived for each year of the analysis period for individual firms and categorized into four types: active pioneer (AP), efficient optimizer (EO), passive observer (PO), and adoptive adventurer (AA). This part of chapter 6 has academic implications in that it quantitatively analyzes routines, important concepts in evolutionary economics but limited in empirical research, through a multidimensional approach to firm behavior and relative comparisons within a sectoral regime.

The second part of Chapter 6 describes the relationship between the four types of innovation routines and the dynamics of technological diversity. Using the results on technological diversity and search patterns from Chapters 4 and 5, this study examines the diversity dynamics for innovation routines. It also investigates when each of the four innovation routines performs the three patterns of technological search.

Finally, **Chapter 7** is the conclusion of this study. By summarizing the results derived from the previous chapters, the study draws policy implications for the endogenous mechanisms of diversity dynamics in technology with respect to technological search and organizational routines. Based on these academic findings, practical suggestions are made for the innovation direction of photovoltaic technology. Finally, the limitations and contributions of this study are discussed, and future research directions are suggested.

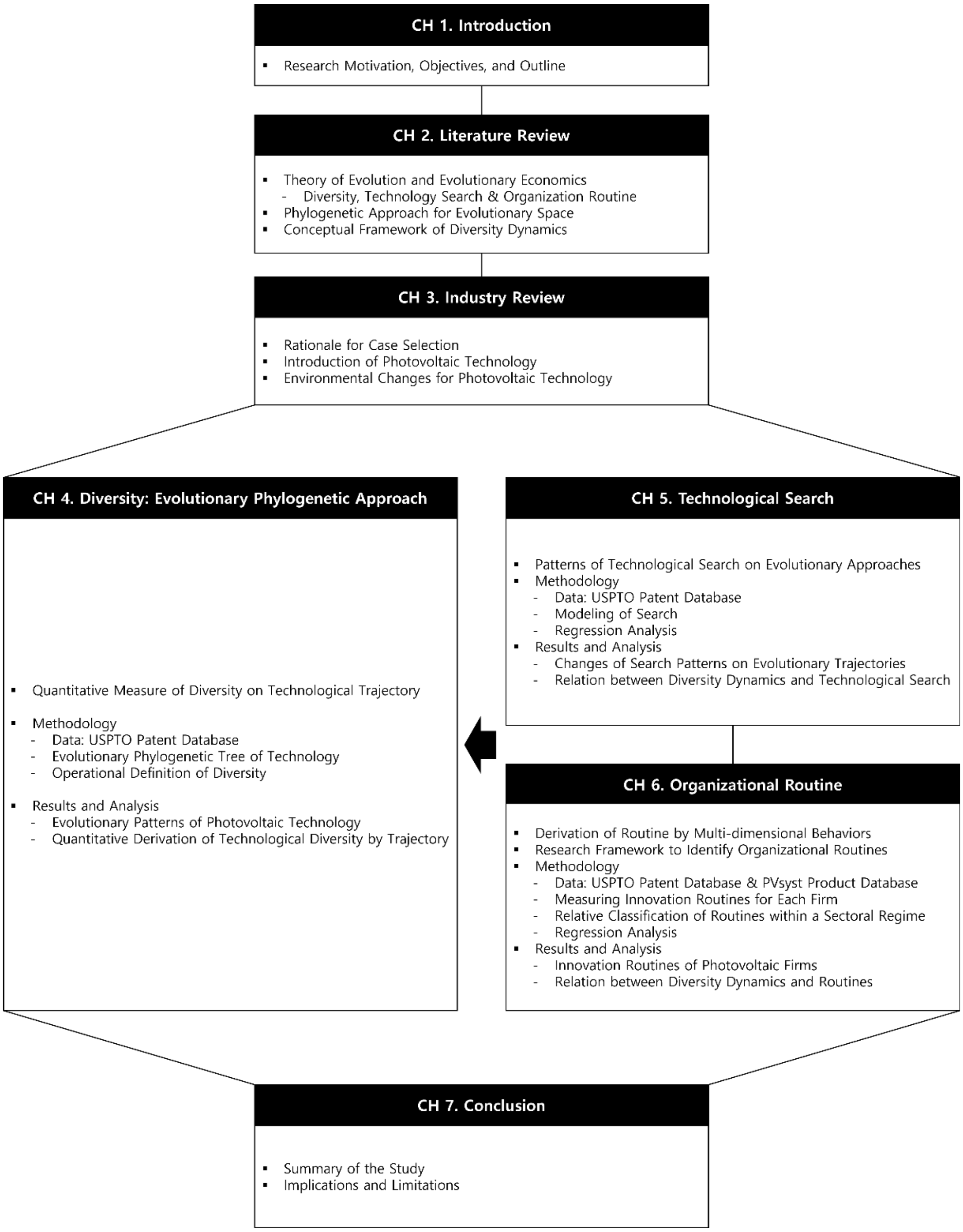

Figure 1-1. Outline of this study

Chapter 2. Literature Review

2.1 Theory of Evolution and Its Generality

The term "evolution" refers to the phenomenon of genetic changes that accumulate over generations, changing the number of individuals and giving rise to new species (Lande & Arnold, 1983). Since Charles Darwin's (1808-1889) of "On the Origin of Species (Darwin, 1859)", theoretical discussions have developed in biology. The core concepts on the theory of evolution are variation, retention, and selection. Evolution occurs when individuals have mutability, replicability, and heritability, and individuals with these traits are subject to a necessary and inevitable process of selection (Smith et al., 1985).

2.1.1 Social Sciences with Evolutionary Approaches

Today, the theory of evolution is widely applied beyond the biological domain. Especially in the social sciences, like economics, active attempts have been made to interpret various changes in society in terms of evolutionary perspectives and principles. Some critics have argued that it is inappropriate to extend the concept of biological evolution to other domains (e.g., Foster, 1997; Penrose, 1952; Witt, 1996). Nonetheless, empirical researchers have been intrigued by the evolutionary nature of socio-economic phenomena and have inductively developed an evolutionary perspective (Nelson, 2006).

In fact, evolutionary propositions about social development predate Darwin, such as Hume (1896), Mandeville (1728), and Smith (1776) (Nelson, 2006). The most prominent example is Adam Smith's "invisible hand," which describes the structure of a market economy as not artificially created by centrally controlled forces (Nelson & Winter, 1982). It establishes that socio-economic phenomena are the outcome of evolutionary processes that have occurred over a long period of time without an ultimate designer, as whether God or man (Nelson, 2006).

The principles of Darwinian evolution have had an enormous impact on the theorization of social evolution, which existed only as an abstract concept. Darwin's seminal contribution to the theory of evolution is the proposal of variation and selective retention as the specific mechanisms by which evolution operates. This is so extensive concept that it has become a very powerful source of understanding not only of changes in the composition and nature of biological species, but also of cultural and social changes in humans (Nelson, 2006). Indeed, Darwin (1859, 1971) suggested that evolutionary principles could be applied to morality and social groups, as well as human languages (Hodgson, 2005). A number of scholars in various fields, such as Bagehot (1872), James (1896), and Veblen (1898, 1899), argued that the Darwinian mechanisms of evolution also apply to mental, epistemological, moral, social, and political evolutions (Hodgson, 2005; Nelson, 2006).

There are three major concepts of evolution shared by the social sciences and biology. The first is the perception of change (Thompson, 2001). The concept of evolution implies change. Evolutionary processes explain the mechanics that led to the current state of complex phenomena in various fields. In other words, the evolutionary perspective is concerned with dynamics, not statics, and emphasizes the irreversible nature of time: everything is bound to change over time (J.-D. Lee et al., 2022). From an evolutionary perspective, a persistent state of equilibrium cannot be maintained, and continuous change is normal (Thompson, 2001). Furthermore, change is not constant, and each change varies in scale, scope, and speed.

Second, evolution is not the equivalent of progress (Gould, 2002). Evolutionary change simply indicates that something is different than before and does not show whether the change is in the direction of progress or regression. Evolution is not purposive, so the outcome is not necessarily optimal. The evolutionary process requires diversity, complexity, and chance. The fact that diversity always exists to choose from implies that selection may not lead to optimal outcomes (J.-D. Lee et al., 2022).

The last concept concerns the speed of evolution (Gould & Eldredge, 1972; Mokyr, 1990; Simpson, 1944). Evolution occurs at different rates, from instantaneous to incremental. All rates of evolution are progressive and continuous at a given scale. In "On the Origin of Species," Darwin repeatedly quotes the Latin maxim "Natura non facit saltum[2]" to emphasize the progressive nature of evolution (Darwin, 1859). However, whether evolution is gradual or radical depends on the time frame and analysis. Modern evolutionary theory recognizes that evolution sometimes proceeds rapidly (Nelson & Winter, 1982). The concepts of radical and revolutionary changes are not antithetical to evolution, just as gradual changes do not necessarily imply an evolution.

[2] It means that "nature does not leap".

Building on this consensus, the 20th century marked as a renaissance of evolutionary approaches to the social sciences. A number of evolutionary social scientists emerged, including Schumpeter (1934), Popper (1959), Hayek (1973), and Campbell (1974). Grounded in their respective disciplinary traditions of philosophy, economics, sociology, and anthropology, their evolutionary explanations became the roots of evolutionary theory in the social sciences (Hodgson, 2004, 2005; Nelson, 2006).

In addition, Dawkins (1983) proposed "Universal Darwinism". This term, which captures the interdisciplinary breadth and generality of evolutionary theory, has served to extend the methodological debate about the application of evolutionary theory to the social sciences to an ontological level (Witt, 2008). Universal Darwinism explains a common ontological basis existing for all systems, including the natural world. Accordingly, any system can be explained by Darwinian principles, provided that variation, retention, and selection are properly defined, even if each domain has its own evolutionary mechanisms (Aldrich et al., 2008; Hodgson, 2001; Knudsen, 2001). The academic works that are based on universal Darwinism and directly utilize the framework of biological evolution to study socioeconomic phenomena have contributed to broadening the horizons of evolutionary social science (e.g., Carignani et al., 2019; Wagner & Rosen, 2014). In the following section, evolutionary economics, the theoretical basis of this study, is introduced among the evolutionary approaches to social science.

2.1.2 Evolutionary Economics

In the tradition of Joseph Alois Schumpeter (1883-1950)[3], evolutionary economics explores economic dynamics from an evolutionary perspective. Schumpeter was concerned with long-term developments and structural changes in modern capitalist economies and emphasized the importance of innovation as a driver of economic growth. His argument for innovation highlighted the role of the entrepreneur and the supply side with the view on supply management economics[4]. In "The Theory of Economic Development (1934)," Schumpeter defined an innovation as a new combination of factors in production. His subsequent work, "Capitalism, Socialism and Democracy (1942)," established the argument that creative destruction and entrepreneurship by firms with incentives to innovate lead to dynamic economic growth (Burlamaqui & Kattel, 2018).

Schumpeter's perspectives on innovation and economic growth can be summarized in three arguments (Aghion et al., 2015). First, innovation is the core engine of economic growth. Second, the profit motive of entrepreneurs to capture excess profits or monopoly power drives innovation through investment. Third, new innovations replace existing ones, causing destruction and creation. The innovation process is endogenous and dynamic.

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[3] From an institutional perspective, the origins of evolutionary economics are often attributed to T. Veblen (Brette, 2003; Jo, 2020). However, this study follows the lineage of J. Schumpeter, and understands evolutionary economics in the neo-Schumpeterian and innovationist tradition of R.R Nelson and S. Winter.

[4] This contrasted with Keynes's theory of effective demand, which emphasized the demand side to overcome the Great Depression (Dabic et al., 2011; Mazzucato & Wray, 2018). In response to the Great Depression of 1929, Keynes argued that governments should stimulate market demand through tax cuts and spending to stabilize the economy in the short term. Schumpeter, on the other hand, pointed to a lack of innovation as the fundamental cause of the recession and emphasized the importance of providing incentives for economic agents to innovate to enhance structural competitiveness in the long term.

Therefore, innovation-driven economic growth has an evolutionary character. Although Schumpeter explicitly refused to link his theory to biological evolution, the economy he described is clearly an evolutionary process (Nelson, 2006).

On Schumpeter's theoretical foundation, evolutionary economics developed as a response of the growing recognition of technological progress as a major source of economic development and reflection on empirical research. Evolutionary economists sought to elaborate on Schumpeter's views by emphasizing innovation and dynamism through evolutionary thinking (e.g., Levinthal, 1998; Nelson & Winter, 1982; Saviotti, 1996).

Evolutionary economics takes a systemic approach to comprehending the cumulative and path-dependent processes of innovation (Nelson & Winter, 1982). By adopting a relativistic view (Samuels, 1995), the various elements of the economy are understood as interrelated and interconnected as a system rather than independent (Edquist, 2010; Malerba, 2004). The theoretical foundations were laid by R. R. Nelson and S. G. Winter in their book, "An Evolutionary Theory of Economic Change (1982)"[5]. Nelson and Winter contributed to overcoming the limitations of earlier evolutionary economics which was restricted to biological analogies, and established a theoretical framework by taking a computational approach to how evolutionary mechanisms operate in economic systems.

[5] The conceptual formation of evolutionary economics predates Nelson & Winter (1982). Veblen (1989) raised the importance of evolutionary thinking in economics, and Alchian (1950) argued that the assumptions of optimality and rationality are unrealistic due to the uncertainty that exists in the economy, and that economic phenomena can be analyzed without these assumptions by adopting Darwin's survival of the fittest.

2.1.2.1 Approaches in Evolutionary Economics and Its Difference from Mainstream Economics

Traditionally, economics assumes "ceteris paribus" and attempts to control variables and simplify models to explain the causality of phenomena[6]. However, contemporary capitalism with liberal market economies is highly complex, diverse, and exhibit a great deal of unpredictable change. Therefore, the answers derived from theoretical models under strong constraints are unlikely to be universal solutions applicable to the real world (Nelson & Winter, 1982).

Evolutionary economics accepts the complexity and uncertainty of the actual economy as it is. Since the economic world is irreversible, historical, and dynamic (Arthur, 1994; Malerba et al., 1999), it develops alternative theories that are distinct from the single optimal solution or general equilibrium of mainstream economics from the perspective of a holistic system. Thus, evolutionary economics aims for appreciative theorizing rather than formal theorizing such as the neoclassical equilibrium model (Nelson, 1995). Appreciative theorizing alleviates the limits of the reality explanatory power of formal theorizing under the perception of reality as it is and pursues the possibility of predicting the future through pattern analysis of the actual economy.

The evolutionary economics approach is characterized by the following features (Hodgson, 1999; Nelson & Winter, 1982).

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[6] A concept introduced by British economist Alfred Marshall (1842-1924) to formulate microeconomic theory, meaning all other things being equal. It is criticized for making very strong constraints on variables for consistent economic analysis, and for being unrealistic. However, it is used as a basic assumption due to its convenience and usefulness in developing economic theory.

First, the methodology of evolutionary economics is based on analogies and metaphors from biological evolution. The key concepts of evolutionary biology, such as variation, mutation, selection, replication, and fitness, are translated into economic concepts such as innovation, imitation, market selection, and market share. However, it should be noted that the reason for adopting concepts from biology is that evolutionary theory is the most advanced in the field. It does not necessarily seek evolutionary links between socioeconomic phenomena and biology. Evolutionary economics considers not only biology but also the evolution of the universe or geological formations, to explore the cumulative and continuous evolution of economies (Nelson & Winter, 1982). In other words, it focuses on the process of economic dynamics itself and uses concepts from evolution to explain it (Hodgson, 1987).

Secondly, it assumes 'bounded rationality[7]' of the actors. Bounded rationality is intrinsic and cannot be overcome by any condition (Nelson & Winter, 1982). it leads individual actors to produce non-homogeneous behaviors and outcomes, and as a result, a wide range of differences are observed within groups (Nelson, 1991; Nelson, 1995; Saviotti, 1991). The heterogeneity within an economic system implies asymmetries in qualitative dimensions such as culture and institutions, as well as quantitative dimensions such as technology, income, and size.

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[7] In the context of evolutionary economics, bounded rationality refers to the notion that economic agents' decisions are limited by cognitive and informational constraints. It originated as a critique of mainstream economics' perfect rationality assumption that agents can process all available information, weigh the costs and benefits of alternative choices, and make optimal decisions that maximize utility. Bounded rationality is a realistic and adaptive approach to decision-making, where economic agents aim to achieve a good enough and satisfactory outcome rather than an optimal one.

Third, interactions are important. Actors in an economic system interact with each other to learn, adapt, reconfigure, and explore options then increase diversity (Stacey, 2001). It evolves together for scientific concepts, technologies, products, organizations, and so on, and each of evolutionary mechanisms on variation, selection and retention are not independent (Ziman, 2000).

For the last, it concentrates on dynamics on the economy. The circumstances around economic actors are always changing (Hodgson, 1987; Hodgson, 1999). Since dynamic change processes involve uncertainty, it is not feasible for a boundedly rational agent to have a perfect foresight of the future. Therefore, it is not possible to maximize behavior and calculate optimal solutions in the mid- and long-term perspectives. Additionally, a process of change involving adjustments and frictions in behavior is out of equilibrium (Nerlove, 1972; Samuelson, 1947). Therefore, using the emergence of novelty in the form of new actors, technologies, products as the basis of analysis, evolutionary economics explains phenomena with concepts such as exploration, routines, and cumulative technological progress (Nelson & Winter, 1982).

2.1.2.2 Innovation, and as Its Indicator, Diversity

Evolutionary economics emphasizes the importance of a technology push for innovation[8]. This perspective stems from Schumpeter's theory of technological innovation,

[8] However, it does not exclude the demand-pull perspective. Nelson & Winter (1977) showed that the creation and diffusion of innovations is also significantly influenced by non-market factors such as public organizations and educational systems, and Dosi (1982) argued that markets have a role to play in selecting innovations that have the potential to succeed among the technological trajectories that exist within a technology paradigm.

described previous section. For Schumpeter, technological innovation serves to bring about business profits from a supply standpoint and is defined as the first introduction and implementation of a change in technology from a commercial standpoint (Schumpeter, 1934). All innovations in evolutionary economics as followed Schumpeter are generated from advances in scientific works through specialized research and development (R&D) activities and the accumulation of knowledge. For example, Rosenberg (1976) used the example of navigation and medical technology to show that the development and application of technology cannot be achieved without the accumulation of sufficient scientific knowledge, and Freeman (1982) argued that the major industries that grew rapidly in the 20th century, such as chemicals, pharmaceuticals, and electronics, developed based on organized scientific research in the professional R&D sector.

The key concern of evolutionary economics is to observe and measure innovation. Innovation in evolutionary economics, which is often associated with variation in evolutionary theory, uses diversity as an indicator. Diversity generates from the accumulation of the results on mutations and gene combinations through the process of variation. In biological evolution, variation is the counterpart of inheritance and retention, and refers to the phenomenon whereby an individual's characteristics differ over time. It includes both non-inherited, temporary changes due to selection pressures and mutations that are passed on to the next generation through genetic changes. Diversity is the result of variation and is "the evolutionary engine (Dopfer, 2001, p.31)" that drives the dynamics of a system.

Moreover, the diversity mechanism is independent of the selection, so it is a critical prerequisite for selection to operate in evolution (Basalla, 1988). This is because if diversity did not exist, that is, if all individuals within a population were genetically identical, with no differences in reproduction, there would be no room for selection to intervene (Sober, 1984). Therefore, evolution deals with the interaction between the generation of diversity and selection and then, can be expressed as the observation of changes in diversity over time (Frenken et al., 1999). The following section reviews the core concepts and accumulated discussions for examining the diversity dynamics of technology from an evolutionary economics perspective.

2.2 Dynamics of Technological Diversity in Evolutionary Economics

2.2.1 Diversity

The concept of diversity in fact played a rather minor role in mainstream economics. As described in the previous section, the neoclassical school presents representative agents and draws logical inferences from simplified and stylized attributes that are common to all types of agents. Therefore, differences between agents are not important in these models[9]. Diversity becomes important when the focus is on why and how equilibrium is broken and how this causes changes in the economy over time, as opposed to the problem of

[9] Exchange economies based on division of labor and trade theorize that differences in opportunity costs, i.e. diversity, lead to comparative advantage. However, this is "a rather limited and well-behaved sort of diversity" (Cohendet et al., 1992: 10). Diversity in this perspective is only the starting point of the equilibrium process for trade, but it does not serve as a long-term driver for the entire system.

maintaining equilibrium, which is addressed by the mainstream economics (Cohendet et al., 1992). Later, with the development of industrial economics in the 1950s and 1960s and the growing interest in heterogeneity in the economy, the concept of diversity has been extensively discussed in innovation strategies and policy instruments to solve economic challenges such as market concentration (Finkelstein & Friedberg, 1967), autonomy (Winner, 1978), technological momentum (Hughes, 1994), entrapment (Walker, 2000) and lock-in (Arthur, 1989) phenomena (Geroski, 1989). Especially, diversity is one of the major concerns in evolutionary economics, which emphasizes the role of technological diversity as a stimulus to innovation (Grabher & Stark, 1997; Landau et al., 1996; Rosenberg & Nathan, 1982).

Evolutionary economics takes diversity as its core concept. A fundamental proposition of evolutionary theory is that the diversity of a system affects its development, and the relative importance of the diversity that survives the evolutionary process changes over time (Gibbons & Metcalfe, 1986). Diversity, based on evolutionary theory, refers to the increasing variety of an economic system through the creation of distinguishable economic “species” such as actors, activities, and objects (Frenken et al, 1999). In other words, it aims to explain the emergence of novelty. Therefore, diversity is used to express and measure the qualitative aspects of change that are central to economic development, such as the composition of the economic system (Cohendet et al., 1992; Frenken et al., 2002; Saviotti, 1991, 1994, 1996; Saviotti & Mani, 1995; Silverberg et al., 1988).

The concept of diversity is used to describe economic agents such as firms and consumers, their behavior, or economic factors such as countries, industries, products, and technologies, depending on the intent and context of the researcher. This study focuses on technological diversity at the micro level. Technological diversity is defined as the range of different technologies or technological trajectories available within a given category, such as an industry or system. It is important in evolutionary economics as an indicator and stimulus for innovation (Grabher & Stark, 1997; Landau et al., 1996; Rosenberg & Nathan, 1982).

Technological diversity contributes to innovation in the following ways. Technological diversity fosters creativity by exposing individuals and organizations to a broader range of ideas, perspectives, and approaches (Hargadon & Bechky, 2006; Hong & Page, 2004). In a study examining the dynamics of problem-solving in a collaborative environment, Hargadon and Bechky (2006) found that groups with diverse technological backgrounds produced more creative product development outcomes. Meanwhile, Hong and Page (2004) found that diverse groups bring a wider range of information, insights, and heuristics to the problem-solving process, resulting in effective and innovative approaches.

The presence of technological diversity enriches the possibilities of new combinations in terms of the knowledge base, increasing the possibility of novel technologies emerging (Turner & Fauconnier, 1999), and allowing cross-fertilization of ideas through knowledge spillover, leading to greater innovation performance. (Almeida & Phene, 2004). Uzzi et al. (2013) argued that interactions between different technological backgrounds lead to idea exchange, knowledge transfer, and cross-fertilization of innovations, while Fleming and

Sorenson (2001) empirically analyzed that inventors with diverse collaborations in the pharmaceutical industry were more likely to create highly cited patents.

In addition, a diverse technology portfolio provides flexibility and resilience to the technology development strategy in an uncertain environment (Rosenberg, 1996). According to a study by Loorbach et al. (2017), multiple technology pathways enhance a system's ability to respond and adapt to changing environments. The presence of various technologies provides alternatives to external shocks and mitigates reliance on a single technology, which can lead to adaptability and resilience.

Regarding the theory of the firm, technological diversity affects the ability of a firm to recombine its existing knowledge with new components. Because technological diversity favors new combinations and transforms dominant knowledge, it particularly increases the likelihood that firms will develop radical innovation capacities (Abernathy & Clark, 1985; Quintana-García & Benavides-Velasco, 2008). Grandstand (1998) argued that technological diversity stimulates firms to generate more innovative ideas. In addition, Leonard-Barton (1992) suggested that technological diversification prevents and alleviates core rigidity that hinders innovation of firms, and Suzuki and Kodama (2004) proposed that technology-based firms should exploit economies of scope through technological diversity for long-term survival and growth.

Regarding the relationship between technological diversity and innovation, some point to the limitation of technological diversity in stimulating innovation in certain contexts. They emphasize that specialization in a specific technology can increase efficiency and productivity (Lacerda and Van Den Bergh, 2016; Van Den Bergh, 2008). The arguments based on resource-based theories highlight that focusing resources and efforts in a specific area can achieve economies of scale and lead to more effective performance. In addition, the path-dependent nature of technology allows for positive feedback loops to form when focusing on a few technologies, resulting in cumulative benefits (Arthur, 1989; Foray, 1997). In line with these arguments, Katz (2002) describes the economics of standardized technologies in the telecommunications industry in the context of reducing costs, supporting interoperability, and fostering innovation. However, these arguments do not dismiss the importance of technological diversity. They can be seen as an alternative perspective that emphasizes certain circumstances or trade-offs that may be prioritized over the promotion of technological diversity.

Technological diversity functions as both an input and an output to the evolutionary process of technology (Stirling, 2007). During this process, the level of technological diversity changes steadily, increasing, stagnating, and sometimes decreasing.

In the early stages of technological evolution, or at the emergence of a new industry, technological diversity increases because the technology or industry is not yet clearly conceptualized and there is a wide range of possibilities and experimentation from various actors (Klepper, 1996). Subsequently, it is maximized during the growth phase of the industry when various technologies compete (Abernathy & Utterback, 1978), and then as the industry reaches maturity, certain designs become advantageous due to the need for standardization, economies of scale, and the pursuit of efficiency, technological diversity stagnates or declines. Because the emergence of a dominant design that is widely selected through market acceptance creates a self-reinforcing cycle that focuses effort and investment around the established design.

Reducing technological diversity traps an industry in a cycle of obsolescence, and eventually leads to decline (Klepper, 1997; Klepper & Graddy, 1990; Klepper & Simons, 2005). However, the dominance of a particular design is not always permanent. When a dominant design or existing industrial structure becomes vulnerable to disruption or change, in other words, when a time-limited window of opportunity[10] that favors novelty opens, new technologies emerge that challenge the old, and then diversity increases again through inter-technological competitions (Perez & Soete, 1988; Lee et al., 2005; Anderson & Tushman, 1990; Lin et al., 2021). The industry is put on a path of renewal rather than decline.

The dynamics of technological diversity have been emphasized as an indicator for the developmental stage of a technology or industry, and as a basis for innovation activities (Gao et al., 2013; Lin et al., 2021; Pavitt, 1998). Governments and firms utilize information on technological diversity and its dynamics as a rationale for the design of innovation policies and the timing of strategic actions (Suárez & Utterback, 1995; Utterback & Abernathy, 1975). However, the concept of technological diversity has been consistently discussed as one of the main theoretical categories in evolutionary economics, our

[10] "Window of opportunigy" was first proposed by Perez & Soete (1988) to refer to the role of the emergence of a new techno-economic paradigm in the leapfrogging of latecomer firms that capitalize on the new paradigm and overtake incumbents. It has since been used in several studies in both a favorable and limited sense where new technologies, approaches, or market conditions enable the entry or success of a new firm or technology.

empirical understanding of it remains limited (Frenken et al., 1999). This study points to two gaps in previous literature that have not been fully explained.

2.2.1.1 Gaps in Quantification of Technology Diversity

Diversity dynamics in technology are the result of strategic actions taken by various agents in the economic development process, and the output of non-optimal satisfaction choice under bounded rationality (Nelson, 2009). Thus, the understanding of technological diversity cannot be simplified into an input-output problem based on static and balanced system views, as in classical economics. A dynamic disequilibrium system perspective that considers the environmental context is required to set up a compelling and achievable technology strategy. However, previous studies that have quantitatively measured technological diversity have been limited by a lack of consideration of this systemic aspect, or more specifically, the space in which technological diversity varies. They have analyzed technological diversity at the aggregate level of industries or other large categories of technologies (Anderson & Tushman, 2018; Gao et al., 2013; Lin et al., 2021; Utterback & Abernathy, 1975).

Technological development is a cumulative process that builds on previous technological advances (Tellis and Crawford, 1981). Such accumulations are shaped as technology trajectories, which come together to form a technology space and serve as a basis for analyzing technology development patterns (Dosi, 1982, 1988; Massey, 1999;

Tellis & Crawford, 1981).[11] Previous studies have described the space of technological evolution as a technological population (Frenken et al., 1999), product population (Saviotti, 1996), technological regime (Schot & Geels, 2007), and design space (Bradshaw, 1992; Dennett, 1995; Frenken & Nuvolari, 2004; Frenken, 2006). Technologies evolve by replication and variation through exploration or movement in these spaces (Frenken et al., 1999; Lee et al., 2016), and technological progress is achieved by the convergence of the developmental trajectories of sub-technologies (Dosi, 1982; Dosi & Nelson, 2010).

The changes in technological diversity derived at the aggregate level and at each specific trajectory may differ. For example, according to a study on the evolution of mobile products by J.-D. Lee et al. (2022), the trajectories of the mobile industry divided into smartphones, pseudo smartphones, and pure feature phones have different evolutionary patterns. The number of products has varied over time, and the changes in the number of products in each trajectory are different. However, when the mobile industry is examined from an aggregate perspective rather than individual trajectories, it can be concluded that the diversity of the industry has generally increased from feature phones in the 90s to smartphones today. Therefore, quantification of technological diversity needs to be based on temporal and spatial information about specific technologies.

This study employs an evolutionary phylogenetic approach to quantify technological

[11] Dosi (1982, 1988) proposed the concepts of technological paradigm and technological trajectory for the cumulative and path-dependent nature of technological development. The technological paradigm is defined as the set of most likely ideas, technologies, devices, materials, etc. for an industry at a point in time that are necessary to augment economic production through technological innovation at that point or in the future. Additionally, the technological trajectory is a set of possible technological directions defined by a particular paradigm.

diversity by considering the specific trajectory of technologies. A detailed description of the methodology is continued in **Section 2.3**.

2.2.1.2 Undisclosed Facts: Access to the Endogenous Mechanism of Diversity Dynamics

Previously, the mechanisms for the generating and change of diversity are mainly intuitive and conceptual explanations based on researchers' insights. Some researchers have proposed that the diversity dynamics are caused by external environmental factors such as consensus on technological concepts (Grodal et al., 2015; Suarez et al., 2015), intra-industry competition (Anderson & Tushman, 1990), and increasing demand heterogeneity (Adner & Levinthal, 2001). However, technology develops and innovates endogenously (Fleming, 2001; Schumpeter, 1942). Moreover, the variation and mutations that generate diversity in evolution are random or blind changes in genes, occurring regardless of the adaptation and survival needs of the individual to its environment. Therefore, a distinction must be made between the process of change itself, which is dominated by external factors, and the mechanisms that fundamentally and endogenously drive the dynamics of diversity (Endler, 1992; Fisher, 1930). In other words, it is necessary to understand the endogenous mechanisms of diversity dynamics, that is, how technological diversity is generated, maintained, and increased or decreased.

The discussion of this point is the origin of this study. This study draws on two perspectives of the technological innovation model (Ma & Nakamori, 2005) to comprehend diversity dynamics. The first one focuses on the nature of the technology itself (Arthur, 1988; Kauffman, 1993). This perspective is the equivalent in biological evolution of being interested in how the physical structure of individuals, such as their DNA, affects their behavior and the future of the species. Complex structures and systems cannot change independently of their relationships to other components of the complex. Some of the changes are biased by structural relationships and forms (Goodwin, 1994). Technological systems also have a high degree of complexity and are structured by scientific relationships between technologies and by economics. Such characteristics of technologies themselves act as a structural constraint on their evolution. Therefore, variations in technology levels and combinations are not infinitely possible (Coccia, 2019a, 2019b; Frenken, 2006; Kauffman & Weinberger, 1989; Wagner & Rosen, 2014).

The second perspective focuses on the actors who generate technological diversity in the real world. Changes in technological diversity are the result of strategic actions taken by various agents such as universities, research institutes, and companies in the development of technology and industry. Evolutionary economics refers to the state of varying differences within a population as heterogeneity (Nelson, 1991b, 2007; Saviotti, 1991). At each level of the economy such as country, industry, and firm, actors are heterogeneous (Nelson & Winter, 1982). Most technologies, which are concrete, complex, and cumulatively developed, tend to be specific to the actors in the technological activity (Dosi & Nelson, 2010; Pavitt, 1998). Technology is a sort of recipe, and even the same technological elements can produce different results depending on the recipe, which in turn depends on the ability of the actors to execute the recipe (Baldwin & Clark, 2000; Dosi & Nelson, 2010). Thus, the heterogeneity of actors is fundamental to the creation of diverse technologies.

To sum up, this study investigates the endogenous mechanisms of diversity dynamics through technological search as the behaviors of recombination in technology itself, and organizational routines[12] as an actor of technological development. the following section describes the theoretical background of evolutionary economics and the discussions in previous studies on technological search and organizational routines.

2.2.2 Technological Search

Technological search is an innovation vehicle. Novel technologies are created through the recombination of technologies (and technological elements), and the process of exploration is inevitably required. However, search does not have an unlimited scope and can be carried out indefinitely. A technology system is a complex system that includes interrelated elements (sub-technologies) intended to collectively achieve one or several goals within a particular structure (Simon, 1969). Hence a technology is defined based on its elemental characteristics, that is, an internal structure, and there is a relationship between technologies (or technological elements) based on physical laws of nature, operating principles, and economics (Frenken, 2006; Frenken et al., 1999). Previous studies have

[12] Organizational routines are recurrent behavioral patterns in organizations (Dosi et al., 2000; Feldman & Pentland, 2003; Geels, 2014; Nelson & Winter, 1982; Winter, 1988). Evolutionary economics uses the concept of organizational routines to understand certain aspects of firm’s behavior, performance, stability, and change. The detailed review of the literature is continued in Section 2.2.3.

argued that technology and technology elements have various relationships, including interdependence, complementarity, and similarity (Fleming, 2001; McNamee, 2013). Due to the interrelationships between technologies (or technological elements), technologies develop into systemic groups rather than independent individuals (Andriani & Carignani, 2014; Coccia, 2019a, 2019b). For example, within mobile products, technologies on LCD and battery are correlated (Windrum et al., 2009), and rear camera technology evolves in dependence on CPU technology (Coccia, 2019b). An ensemble of technologies should be evaluated at the system level to assess the impact of each single technology on the overall system, which again raises the issue of complexity (Frenken, 2006). Therefore, the nature of technology itself, described above, serves as a structural constraint on technological evolution (Coccia, 2019a, 2019b; Kauffman & Weinberger, 1989; Wagner & Rosen, 2014). The NK model allows to sketch the evolutionary search and diversity generation process under such structural constraints[13]. The following description is based on Frenken (2006).

The NK model consists of two basic parameters, N and K. In a technological system, parameter N is the number of technologies (a kind of genes) and parameter K is the

[13] The evolutionary properties of complex systems have been a longstanding subject in biology (Kauffman, 1993). The interdependence of genes refers to the complex relationship between the genotype and phenotype of an biological organism. In evolutionary mechanisms, variation and retention occur at the genotype, the set of genetic information, while selection occurs at the phenotype, the totality of traits that constitute an organism's fitness. The complexity of organisms means that mutations in one gene can change its functional contribution to the overall phenotype, as well as can also affect genes that are interrelated to the phenotype. For this reason, the original gene set imposes structural constraints on the possible directions of further evolution. In this aspect, biological evolution can be conceptualized as a search process in the space of gene sequences guided by the fitness landscape, a mapping that assigns a measure of reproductive value to each genotype (De Visser & Krug, 2014; Svensson & Calsbeek, 2012). First proposed by Kauffman & Weinberger (1989), the NK model is a stochastic model of a genotype-fitness landscape that represents the general features of interaction between genes in complex system. It provides a simple model and simulation of how evolution occurs in the presence of contradictory constraints through the interactions between genes and the resulting fitness landscape of genotypes (Kauffman, 1993).

interrelationship between technologies based on the laws of natural science (epistasis of genes)[14]. Systems without epistatic relation are when K=0, whereas systems with maximum complexity, which means all elements have epistatic relations are when K=N-1. The effect of epistasis is examined by construction a fitness landscape. The evolutionary fitness landscape is formed by values of N and K, and is like a topography of mountains and valleys, ruggedness is measures of fitness. besides it has the property of constantly changing rather than being stationary (Kauffman, 1995).

In the NK model, the evolutionary optimum corresponding to innovation is derived from a combination of technologies through search. Since search is a time-consuming and costly process, there is a tradeoff between the input of resources and the output of the search, which determines the scope of the search at an economically feasible level. In addition, search is based on the past, not a perfect prediction. After a search is performed, if it yields good results compared to past results, more inputs are added; otherwise, fewer inputs are added, giving it a path-dependent nature (Dosi & Nelson, 2010). In the end, In the end, due to technological interactions and economics, a local optimum rather than a global optimum is derived. Diversity is generated by the number and distribution of local optima and the differences between them (Frenken, 2006).

[14] In biology, a single gene is able to generate multiple traits (pleiotropy) or multiple genes are possible to develop only one trait (polygeny). Moreover, a variation in a gene may have either a positive effect on some traits or a negative effect on others. This phenomenon is called epistasis, the relationship between genes (Frenken, 2006).

2.2.2.1 Patterns of Technological Search in Previous Literature

Several studies have been conducted on the patterns and quantification of technology search. Researchers mostly described search methods employed based on one-dimensional distance concepts, such as near and far in technological relevance or similarity (Helfat, 1994; March, 1991; Martin & Mitchell, 1998; Miner et al., 2001; Stuart & Podolny, 1996; Von Hippel & Tyre, 1995). On the other hand, Katila and Ahuja (2002) expanded the technological search behavior of firms into a two-dimensional framework of scope and depth. Specifically, the scope aspect refers to the search for new technological knowledge that does not exist in a firm, while the depth aspect refers to the deepening of existing technology that the firm owns. Building on this work, several subsequent studies have applied the concepts of scope and depth on technological search (Caner & Tyler, 2015; Grimpe & Sofka, 2009; Laursen & Salter, 2006; Wu et al., 2014; Zhou & Li, 2012). Taking innovation perspective in a comparable context, Cecere et al. (2015) and Koski and Kretschmer (2007), who took the perspective of innovation, defined the introduction of new technological elements of a product as horizontal innovation and the enhancement of existing technological elements of a product as vertical innovation.

While these studies contribute to a more multidimensional view of search by departing from the traditional notion of distance, they are limited by the discussion of inter-technology relationships described above. Technological search is performed historically on a fitness landscape shaped by technological relationships. In other words, a technological search takes place within the space where technology trajectories are forming;

therefore, it is necessary to consider not only the distance but also the direction of the search (Katila and Ahuja, 2002; Koski and Kretschmer, 2007).

The directions in which current technologies have been shaped by the past will guide the evolution of future technologies. More specifically, even if technologies are recombined according to the same approaches to technological search, there may be differences in the nature of the newly introduced technologies depending on the search pattern. These differences, in turn, will reflect the relationships between technologies, leading them to evolve in distinct directions. For example, colors, calculators, and www capability are some of the new technologies introduced in mobile products by 2003 (Koski & Kretschmer, 2007). All of these technologies were recombined with existing mobile technologies through horizontal innovation, i.e., search in terms of scope, but each of them has different technological characteristics. In detail, color belongs to the design aspect, calculator to the computational aspect, and www capacity to the communication aspect of technology. Such differences guide the subsequent evolution of these technologies toward design, computation, and communication, respectively.

As discussed so far, there are still lack of exploration in the literature on technological search. To clarify the endogenous mechanisms of diversity dynamics, technological search needs to be further refined to include direction as well as scope and depth. This study explores the evolutionary process by which individuals acquire genetic diversity to find clues to technology search. Further research on technological search and diversity dynamics in technology is continued in **Chapter 5**.

2.2.3 Organizational Routines

Agents in technological development play an important role in the evolution of technology. They are heterogeneous, and each selecting technological elements to innovate within a portfolio of accessible technologies, and strategically developing technologies accordingly (Nelson & Winter, 1982). The decisions of actors are guided by bounded rationality, leading to each of different satisficing choices that is not optimal. In this iterative process, heterogeneity persists, and the evolution of technology depends on heterogeneous actors (Frenken, 2006; Nelson & Winter, 1982; Posen et al., 2013).

The presence of actors and their intentionality in technological evolution is one of the major criticisms to evolutionary economics (Foster, 1997; Penrose, 1952). The main issue in the debate is whether innovations generated by actors contradict the blind nature of variation in evolution. To begin with, Darwinism does not exclude intentionality on the part of the actor, and just because variation is blind does not mean that it is not intentional (Vromen, 2004). The essence of Darwinism is that everything must be causally explained. So, if something can be described in a causal way, it is the outcome of an evolutionary process (Cordes, 2006; Hodgson, 2004; Witt, 2003). In the economic domain, innovative activities can be driven by the needs of the actors. However, it is not always successful and often produces unintended consequences (March, 1963). And as in the evolution of organisms, only selected innovations are maintained and transmitted. Thus, despite the presence of actors and their intentions, technological evolution is causally explainable based on evolutionary theory, and innovation does not conflict with the random nature of variation.

This study focuses on firms among the various actors for technological evolution. In evolutionary economics, a firm is an organization composed of various individual economic actors in a hierarchical order, and an entity that continuously operates, adapts, and evolves in business, in historical time and specific space (Jo, 2006). It is considered a goal-oriented and profit-seeking organization, not an organization that maximizes profits, as defined by mainstream economics (Winter, 1988). In addition, firms select technological elements from their accumulated technology base and turn them into products. Through products, they reflect market preferences back into technology (Lee et al., 2021; Nelson & Winter, 1982). In this way, they directly intermediate technology and the market.

Technological diversity in terms of firms can be defined as the diversity of knowledge systems and principles underlying the nature of their products and production methods (Quintana-García & Benavides-Velasco, 2008). In other words, it is related to the extension of a firm's technological capabilities to a wider range of technologies and knowledge areas (Grandstand & Oskarsson, 1994). Previous studies have analyzed patent data and found some consistency in the way firms diversify their technological capabilities (Piscitello, 2000, 2004; Valvano & Vannoni, 2003). Thus, from the actor perspective, the consistency with which firms broaden their technological capabilities is related to the endogenous mechanism of diversity dynamics in technology.

The theory of the firm from an evolutionary economic perspective [15] takes the

[15] In evolutionary economics, the theory of the firm is the dynamic study of the birth, growth, and extinction of heterogeneous firms. Through a non-reductionist approach, it acknowledges the unique significance of

organizational routines[16] of the firm, rather than the firm itself, as the basic unit for grasping the firm. Through the lens of capability, organizational routines are the bearers of knowledge and activities for innovation and production (Baldessarelli et al., 2022; Parmigiani & Howard-Grenville, 2011). Firm behavior is described by routines, and firms are understood through what routines they have and how they change over time (Dosi & Nelson, 2010).

2.2.3.1 Revisiting the Concept of Routines on Evolutionary Perspectives

The term of routine was first introduced by Stene (1940) as a part of some organizational activity that has become habitual, and the Carnegie School established the foundation for the study (e.g., Cyert & March, 1963; March & Simon, 1958). Nelson and Winter's seminal book, "An Evolutionary Theory of Economic Change," is recognized as a pioneer in routine research. Their work sparked academic interest in the concept of routines and stimulated subsequent research (Baldessarelli et al., 2022; Becker, 2004; Parmigiani & Howard-Grenville, 2011).

Evolutionary economics scholars have come to comprehend certain aspects of firm behavior, performance, stability, and change through the concept of routine. Organizational

firms as goal-oriented organizations, as distinct from individuals (Herrmann-Pillath, 2002). Evolutionary economics examines the actual and observable behavior of firms in the real world, placing technological and organizational innovation and production processes at its center (Winter, 1988).

[16] According to the consensus of scholars, "routine" is a term at the collective level as corresponding to "habit", which represents the behavioral pattern of an individual (one person) (Becker, 2004, 2005; Dosi et al., 2000). Therefore, the term "routine" used throughout the text means "organization routine" without further explanation.

routines are recurrent behavioral patterns of an organization (Dosi et al., 2000; Geels, 2014; Nelson & Winter, 1982; Winter, 1988). Routines are a kind of organizational memory that appear repeatedly in a firm's production, investment, and innovation activities, and stores the firm's knowledge, capability, and experience. Firms act on a particular routine that determines their competitive performance. Routines do not necessarily produce optimal results but are the best adaptations for dealing with uncertainty (Dosi & Nelson, 2010). In addition, firms with limited rationality make satisfactory choices at every moment; thus, they maintain their existing routine as long as it leads to satisfactory results. Routines are accumulated based on a firm's experience; therefore, it is a unique characteristic that other firms cannot imitate and is the source of firm heterogeneity (Day, 1994; Dierickx & Cool, 1989).

Nelson and Winter (1982) emphasize that routines are fundamental components of organizational behavior and play an important role in shaping how organizations interact with their environments (Nelson & Winter, 1982). Since Nelson and Winter drew an analogy between routines and genes in biology, routines have been treated as the gene or genotype[17] of a firm from an evolutionary perspective. (e.g., Hodgson, 2003; Hodgson & Knudsen, 2004; Nelson & Winter, 1982; Winter, 1995). Genes and genotypes in biology are genetic information, and a set of them can control the development and behavior of an

[17] A gene is the basic unit of heredity, which in biology means a section of deoxyribonucleic acid (DNA). Each gene exists in a specific location on a chromosome, a thread-like structure made up of DNA, and is arranged along the chromosome. A genotype is the genetic composition of an individual, representing a specific combination of genes. Genotype is responsible for various traits and characteristics of an individual and determines an its genetic potential.

entity and can be passed on to the next generation. They indicate how different or unique an individual is from others within the same species and determine its outward characteristics (Griffiths et al., 2002). Organizational routines, such as the genes/genotypes of firms, also determine (i) how different or unique a particular firm is from other firms in the same sector and (ii) behavior, which is an extroverted characteristic of firms.

2.2.3.2 Routines as Recurrent Behavioral Patterns of Firm

Specifically, (i) routines are inherent and static characteristics of firms (Day, 1994; Dierickx & Cool, 1989). One unanimously agreed upon point in the routine literature is that nothing becomes routine without recurring occurrences (Becker, 2005b). Recurrence is a hallmark of routines (Becker, 2004; Cohen et al., 1996). According to the Cambridge dictionary, recurrent means "happening again many times," that is, something in the t-1 period also exists or occurs in periods t and t+1. During biological evolution, the replication and inheritance mechanisms of genes arising from genotypes correspond to the recurrent characteristics of the routine (Johannsen, 1911; Lewontin, 1974). Consequently, routines stabilize organizations over time. In other words, the difference between the behaviors of periods t-1, t, and t +1 decrease (Cohen & Bacdayan, 1994; Feldman & Pentland, 2003; Nelson & Winter, 1982). On the other hand, even if external conditions change, the stability of routines and behaviors are maintained; thus, routines sometimes act as a resistance to change (Howard-Grenville, 2005; Kilduff, 1992; Nelson & Winter, 1982). Therefore, the endogenous stability or statics of routines contributes to a firm's tendency to make satisfactory choices. Firms adhere to their current routines as long as they are satisfied, even if the results are not optimal (Geels, 2014).

Paradoxically, firms adapt by changing their routines according to external environment dynamics. Firms that succeed in changing their routines are selected by the market as innovative. Routines change endogenously through feedback on outcomes based on past routines (Becker et al., 2006; Nelson & Winter, 1982; Winter & Szulanski, 2000), and the path of change in routines generated by such processes (Garud et al., 2010; Rerup & Feldman, 2011) explains organizational and economic changes (Adler et al., 1999; Feldman, 2000; Miner, 1991). Endogenous changes in routines that correspond to mutations in evolution occur gradually over long periods of time (Cohen et al., 1996; Levitt & March, 1988). Radical changes are avoided in evolution because mutations above a certain level cause dissonance in adaptation to the existing environment, which is unfavorable for survival or does not leave offspring (Bowonder et al., 2010; Kardong, 2005).

Consequently, routines are formed by history in a path-dependent manner (Dosi et al., 1992; Malerba & Orsenigo, 1996; Nelson & Winter, 1982) as the basis for endogenous stability and change in firms for environmental adaptation (Parmigiani & Howard-Grenville, 2011). Therefore, routine reflects a firm’s past empirical wisdom (Gavetti & Levinthal, 2004), which makes it a unique characteristic that other firms cannot imitate (Day, 1994; Dierickx & Cool, 1989).

On the other hand, (ii) routine is a determinant of firm behavior (Hodgson, 2003; Nelson & Winter, 1982). In other words, routines interact with environmental factors to determine firm behavior (Becker, 2005a, 2005b; Hodgson, 2003; Nelson & Winter, 1982)18. Firms act based on a specific routine in response to a given environmental situation at every moment. It seems that a firm's behavior is induced by the environment, but it is routine, as the gene or genotype of a firm that fundamentally determines the behavior. Felin and Foss (2011) asserted the endogenous generation of abilities and behaviors and emphasized the role of routines by citing the "pet bee" hypothesis of Chomsky (2002)19. Routines are the generating principle of regular conditional mechanisms and the source of firms' repetitive behavior (Hodgson, 2003). Routines include forms, rules, procedures, customs, strategies, and techniques underlying the composition and operation of an organization (Levitt & March, 1988), and allow the organization to act repeatedly in response to external environments under any learned context (Cohen et al., 1996). Previous studies have considered routine as organizational memory (Nelson & Winter, 1982), capability (Cohen et al., 1996), heuristic (Becker, 2005b), potential, or disposition (Hodgson, 2003; Knudsen, 2002), and have pointed out routines as the determinants of behaviors.

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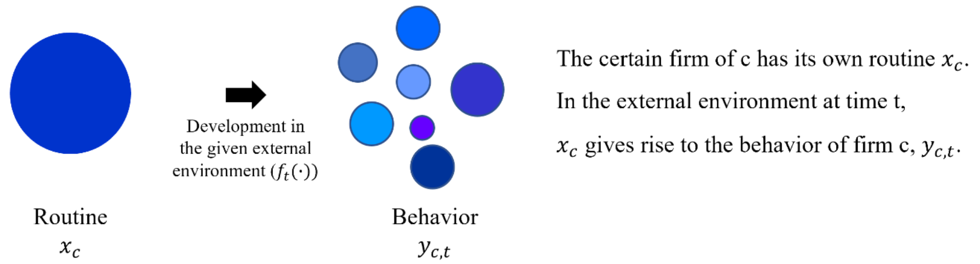
[18] This is a biological analogy, similar to how routine as a gene or genotype develops the firm's behavior as a phenotype. The relationship between genotype and phenotype in biology is a topic of ongoing discussion, and recent studies recognize that the genotype interacts with various environmental factors during development to generate a phenotype as the most realistic model (Wagner & Altenberg, 1996; Pigliucci, 2001). The reason for differences in appearance and behavior with same genotypes, such as identical twins, is that genotypes interact with external conditions to develop phenotypes. Similarly, even though phenotypes are alike, such as foxes and wolves, their genotypes are not necessarily the same because this is the result of the action of external variables (Griffiths et al., 1999). However, it is the genotype that fundamentally determines the phenotype of an individual. For example, no matter what environmental conditions are given, a cat or a dog cannot be born from a human genotype.

[19] Chomsky's (2002) "pet bee" hypothesis: Assume a "pet bee" that always exists in the child's imagination. Child and bee are exposed to the same environment and stimuli. However, despite uniform environmental stimuli, child and bee derive fundamentally different outcomes of behavior (Weiner & Palermo, 1974). The child will not develop the bee's navigational ability and the bee will not develop the language ability. No matter how external environmental conditions are reinforced, it will not help bees learn to speak, and a child's ability to navigate will not be comparable to bees (Felin & Foss, 2011)

Figure 2-1 shows the two characteristics of the routine derived from the literature review as mathematical concepts. In summary, routines are (i) inherent and static characteristics of a firm, and (ii) determine its behavior.



$$f_t(x_c) = y_{c,t}$$

where, f_t : External environment at time t

x_c : Routine of firm c

$y_{c,t}$: Behavior of firm c at time t

Figure 2-1. Conceptual diagram of organizational routines

In summary, organizational routines are formed cumulatively and path-dependently based on the results of past firm behavior. They serve to ensure continuity and stability of the firm through the repeated patterns of behavior (Becker, 2004). On the other hand, they are also responsible for adapting to the constant changes in the external environment and making gradual improvements, opening up the possibility of new behaviors when faced with unsatisfactory market results. In addition, organizational routines serve to generate ongoing heterogeneity and dynamism in the economy (Dosi, 2000). Because firms follow their own distinctive routines, the outcomes are different. Therefore, even if they are performing the same technology in the same industry, the dynamics of technological diversity will be different depending on which routine the firm developed the technology with.

In the following section, the evolutionary phylogenetic approach is introduced. This methodology is used in this study to examine the dynamics of technological diversity in technology exploration and organizational routines in space and time.

2.3 Approaches for Technological Trajectories

2.3.1 Technological Trajectory

2.3.1.1 Concept of Technological Paradigm and Trajectory

A technology is in fact a set of specific knowledge, objects, practices, and experiences, and this set of knowledge forms a technological paradigm. The concept of a technological paradigm as presented by Dosi (1982, 1988) is derived from Kuhn's paradigm theory (1962). It is defined as "a model and a pattern of solution of *selected* technological problems, based on *selected* principles derived from natural sciences and on *selected* material technologies" (Dosi 1982: 152, emphasis in original). In other words, it is a common outlook for solving technological problems in a particular period or era (Dosi, 1982; Constant, 1980), and can be defined as a set of the most likely ideas, technologies, devices, materials needed to increase economic production through technological innovation at that time or in the future for a certain industry at a certain point in time (Dosi & Nelson, 2010). Technological paradigms have a design concept as a solution to a problem, so products that reflect the paradigm of the time will have a similar look and performance.

Technological development is a cumulative process that builds on previous technological advances based on technological paradigm (Sahal, 1985; Tellis & Crawford, 1981). The paradigm-limited scope of exploration and knowledge sharing within a technological ecosystem, and the resulting adherence to a particular paradigm, give rise to certain tendencies in technological development and form a technological trajectory (Castaldi et al., 2009; Dosi & Nelson, 2010). The technological trajectory, proposed by Dosi (1982; 1988) along with technological paradigms, is a set of possible technological directions prescribed by a particular paradigm, and defined as a path or pattern of technological development and change over time. It also implies a sense of direction, such as a feedback loop, generating feedback and learning through the implementation and use of existing technologies (Dosi, 1982; Carlsson & Stankiewicz, 1991; Castaldi et al., 2009). While technology trajectories serve to reduce future uncertainty, they cannot eliminate inherent Knightian uncertainty[20] (Dosi & Nelson, 2010). Technological paradigms and trajectories are not static, but rather change over time. As paradigms shift, so do technological trajectories.

Within a technological paradigm, multiple trajectories are possible. Not all trajectories generate industrial success, but innovators must choose a particular trajectory.

[20] Knightian uncertainty, also known as true uncertainty, is a concept first introduced by Frank H. Knight in "Risk, Uncertainty, and Profit (1921)". In traditional decision theory, risk is a measurable risk in situations where probabilities can be assigned to possible outcomes. However, Knight argued that there are uncertain situations where probabilities cannot be assigned or calculated due to the lack of reliable data or the presence of unpredictable events. These uncertainties occur in complex and dynamic environments, where deep uncertainty and ambiguity make it difficult or impossible to estimate the probability of potential outcomes.

Technological trajectories provide a theoretical foundation for deriving technological characteristics to understand the basis for differential patterns of competition and R&D activity across industries.

2.3.1.2 Methodology for Technological Trajectory

Scholars have attempted to analyze the patterns of technological development through the derivation of technological trajectories based on quantitative and scientific methodologies. This section presents two commonly used methodologies, the principal component analysis (PCA) and patent network analysis.

First, PCA was used in Savtotti and Trickett's (1992), the first study to construct an evolutionary trajectory quantitatively and empirically. They examined the evolution of a helicopter technology that flourished in 1940 and was largely eliminated and replaced by other technologies by 1984. In this study, the evolutionary trajectory of the helicopter was visualized by performing PCA on the six technical characteristics, reducing them to two dimensions and plotting them on a plane.

This methodology has also been applied to tanks by subsequent researchers (Castaldi et al., 2009; Kim et al., 2021). Castaldi et al. (2009) studied the development of tank technology between 1915 and 1945 and found that tank designs from different countries exhibited a high degree of redundancy and similarity along a common technological trajectory. In addition, Kim et al. (2021) derived the dominant design of tanks based on product evolution theory and argued that the interaction between scientific, technological, and social factors drives product evolution.

The PCA methodology can simplify complex datasets and highlight the most important patterns and changes by reducing high-dimensional data to a smaller number of principal components. It also has the advantage of being an unsupervised approach, requiring no prior knowledge or labels, and being easy to explore and visualize data in a low-dimensional space (Jolliffe & Cadima, 2016; Vidal et al., 2016).

On the other hand, this methodology has the limitation of assuming a linear relationship between variables and treating all principal components equally in their contribution to the variance. It also does not explicitly consider the temporal dimension. Technological progress involves complex and non-linear relationships, and some components may be more important than others. Furthermore, ignoring time dependencies can overlook important patterns, trends, or transitions that occur over time in a technological trajectory. Lastly, the possibility that some information from the original dataset may be lost in the process of dimensionality reduction of the variables, thus weakening the explanatory power, is also a shortcoming of the PCA methodology.

The second method utilizes patent citation information or patent codes, like cooperative patent classification (CPC) and international patent classification (IPC), based on network analysis methodology to identify technology trajectories. The patent network model derives technological trajectories by building a network with patents or patent codes representing technologies as nodes and citation relationships or similarity between them as links (Li et al., 2017; Song et al., 2019). Verspagen (2007) empirically analyzed fuel cells by adding main path analysis to patent citation networks and found that technological trajectories are formed selectively and cumulatively. Fontana et al. (2009) traced the technological trajectory of the LAN device industry through a patent citation-based weighted network using the citations of patents as weights. Their approach is advantageous in identifying high-potential patents that are likely to exist in strategic positions along the technological trajectory but are currently under-cited. Erdi et al. (2013) attempted to predict emerging technologies by utilizing a hierarchy analysis on the network represented by a vector of fields cited by each patent. However, hierarchy analysis does not assume a point-in-time analysis, so it is difficult to say whether the technology trajectory is derived.

On the other hand, Song et al. (2019) built a patent network using technology codes rather than patent citations. They analyzed the evolution of hybrid electric vehicle technology by building a technology space map with CPC codes of patents as nodes and similarity between CPC codes as links. This study is unique in that it identifies the process by which engineers in one domain find new solutions to problems and expand their scope to additional technologies beyond their original domain, but it is limited by the dependence of its findings on the segmentation of the technological code.The main advantage of the patent network methodology is that it allows for longitudinal analysis. With patent information accumulated over a long period of time, technological trajectories can be studied over time. In addition, patent data contain a wealth of information such as title, abstract, and applicant, making it easy to draw contextual implications (Borgatti et al., 2009; Verspagen, 2007; Yoon & Park, 2004). However, not all inventions and innovations are represented by patents, and there are often significant time lags in the filing, granting, and citing of patent data. Furthermore, for patent citations, it has a critical assumption that they express meaningful connections between technologies and are indicative of patent influence or prior art. All of these limitations can lead to biased representations of technological trajectories based on patent network analysis (Borgatti et al., 2009; Song et al., 2019).

2.3.2 Evolutionary Phylogenetic Methodology

Recently, several studies on technological trajectories have attempted to overcome the limitations by applying an evolutionary phylogenetic approach to better capture and represent the complexity, non-linearity, and time dependencies inherent in technological trajectories (Chavalarias & Cointet; J.-D. Lee et al., 2022; Li et al., 2017; Zhang, Zhang, et al., 2017). The evolutionary phylogenetic tree in biology is a network that consists of taxa with genetic homogeneity as nodes, and evolutionary relationships between taxa as links (Huson & Bryant, 2006; Santamaría & Therón, 2009). Evolution corresponds to navigation or movement in evolutionary space, an abstract space created by genetic factors. Thus, biologists build evolutionary phylogenies to identify the lineages from which organisms evolved and to explore patterns in the evolutionary process. Similarly, in the study of technological innovation, the construction of evolutionary phylogenetic tree in technology can be used to derive the trajectory of a technology's evolution (Carignani et al., 2019; Cattani & Mastrogiorgio, 2021). This illustrates the dynamic changes in the technology taxa. There are two ways to construct an evolutionary phylogenetic tree in technology. The first is to define a single entity as a node in the phylogeny. Examples from the literature include mobile products (Khanafiah & Situngkir, 2006), jet engine components (Carignani et al., 2019), and brass instruments (Ilya Tëmkin & Niles Eldredge, 2007). In the second, a group called a taxon is derived based on similarity and homogeneity and defined it as nodes. Chavalarias and Cointet (2013) constructed the phylogenetic tree for a set of keywords in research articles, and J.-D. Lee et al. (2022) for a set of mobile products. This study takes the latter approach to observe the collective evolutionary flow of technologies and to grasp the diversity dynamics of technology through it.

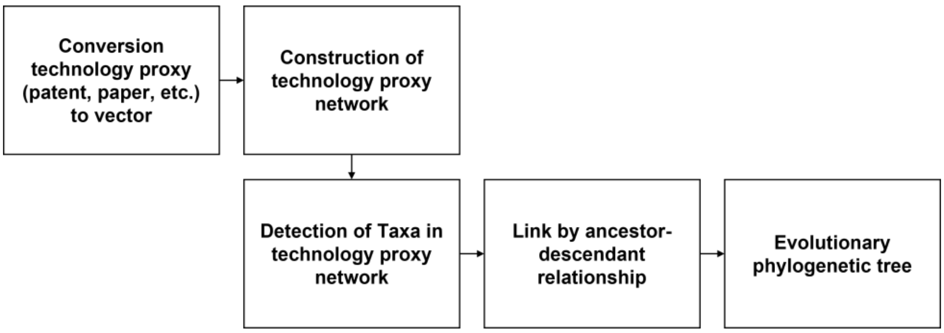


Figure 2-2. Algorithm flow diagram for an evolutionary phylogenetic Tree

The process of constructing a phylogenetic tree from homogeneous taxa is shown in **Figure 2-2**. First, derive the population of products, research articles, patents, technological keywords, etc. that exist at a specific time (Li et al., 2017; Wu et al., 2021; Zhang, Zhang, et al., 2017). Then define them as technological taxa based on their technological homogeneity (Lee et al., 2022). After by matching and linking ancestor-descendant relationships between technology taxa, the construction of evolutionary phylogenetic tree in technology is completed (Chavalarias & Cointet, 2013; Lee et al., 2022). Chavalarias and Cointet (2013) extracted technological terms from the abstract in research articles by the natural language processing technique, and derived groups of technological terms that existed at each period by the Clique methodology. And then the evolutionary process of technology was observed by connecting the ancestor-descendant relationship between them. J.-D. Lee et al. (2022) drew an evolutionary phylogenetic tree for mobile products by identifying taxa with technological homogeneity for each year and deriving ancestral relationship between them. Based on the constructed phylogenetic tree, they examined differentiation and development of smartphones, as a new mobile product group, in the early and mid-2000s.

The methodology for constructing a technological evolutionary phylogenetic tree is a type of network methodology. However, the second approach of evolutionary phylogenetic methodology differs in that it derives technology populations, i.e., taxa, based on technology genes, and uses them as the basic unit to construct technology evolutionary trajectories. PCA and patent networks analyze individual products, patents, and technology codes, which means that existing studies use explicit populations as the unit for observing technological change.

Evolutionary phylogenetic analyses that derive clusters of accumulating variation based on the homogeneity of technological genes and build trajectories based on them are likely to observe the sprouting of new innovations. As a concrete example, Apple's portable media player, the iPod, has been discontinued, but it's technologies of portable music playback, user interface and navigation, iTunes integration, sound quality, etc. have been transferred to the iPhone. Using an explicit technological group, each model of iPod in this case, for the unit of analysis, it is difficult to observe the flow of technology and the convergence of technologies that resulted in the new device, the iPhone.

In addition, it has the advantage of providing an in-depth explanation of the phenomenon of technological development based on the similarity between evolutionary processes in technology and biology (Carignani et al., 2019; Cattani & Mastrogiorgio, 2021). Technological progress and biological evolution share commonalities (Basalla, 1988), and evolutionary stylized facts observed in biology are also found in technological innovation (Wagner & Rosen, 2014)[21]. To better understand the complex and uncertain behavior of technological progress, the framework of biological evolution can be used.

Furthermore, drawing technological trajectories through evolutionary phylogenetic methodology has the following advantages (Carignani et al., 2019; Cattani & Mastrogiorgio, 2021; Chavalarias & Cointet, 2013; J. -D. Lee et al., 2022; Santamaría & Therón, 2009).

First, an evolutionary phylogenetic approach considers the historical context of technological development. This can reveal the driving forces and actual events that shaped

[21] Based on universal Darwinism, Wagner and Rosen (2014) proposed the following nine stylized facts that biological evolution and technological innovation share: Trial and error within population, extinction and replacement, descent with modification, horizontal information transfer, combinatorial innovation, exaptation, ecosystem engineering, episodic change, and multiple and singletons.

the technological trajectory. It also allows us to understand the cumulative nature of technological progress and the flow of innovation by identifying ancestral technologies to current and analyzing common features or functions among different technologies.

Second, based on evolutionary theory, phylogenetic methodology facilitates the classification of technologies based on evolutionary relationships, analogous to biological taxonomy. This can help organize and structure the technology landscape and identify clusters or groups of related technologies. It also enables comparative analysis between different technologies or technology domains. In addition, by identifying who the direct and neighboring ancestors of currently existing technologies are, patterns of innovation can be verified, such as whether current technological advances are driven by deepening existing technologies or by recombination with other technologies (Carignani et al., 2019; Youngblood et al., 2021).

Third, it is possible to predict potential directions for future technological trajectories based on the past. This is because technologies evolve in a path-dependent manner. Analyzing speciation patterns can infer the direction of evolutionary change in different trajectories, and detecting convergent evolution provides possibility to predict which lineages will dominate in the next generation (Huson & Bryant, 2006; Santamaría & Therón, 2009). Furthermore, by observing the formation of new lineages in technological phylogenetic tree, it is possible to figure out the divergence of new technologies (J.-D. Lee et al., 2022; Levinthal, 1998). Therefore, the evolutionary patterns of technologies observed in the phylogenetic tree can be used to draw implications for future developments.

Lastly, an evolutionary phylogenetic tree is a powerful tool for visually representing the evolutionary patterns of technologies and the evolutionary relationships between them. By illustrating patterns such as connections and branches between technologies, it is possible to identify important technological transitions, understand interdependencies between technologies, and effectively articulate the complex processes of technological evolution.

There are also unresolved limitations to the phylogenetic tree methodology. Especially, subjectivity in the interpretation of evolutionary phylogenetic tree is a major concern. It is important to have transparent and objective criteria to mitigate bias when defining traits or features for building evolutionary relationships, or when interpreting evolutionary patterns and relationships that can be very complex.

2.4 The Conceptual Framework of Diversity Dynamics in Technology

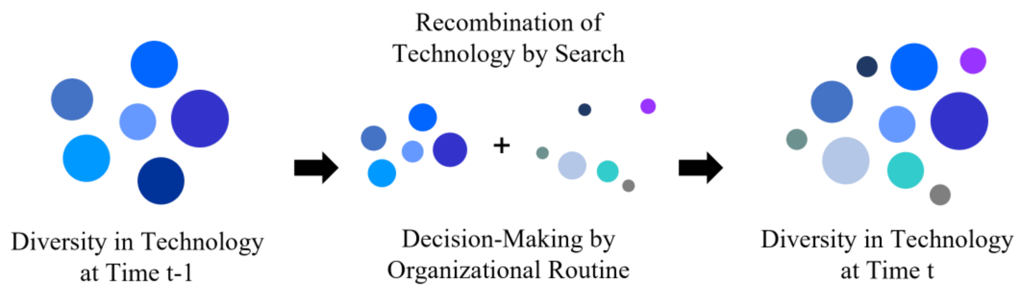
How is technological diversity, as an indicator of innovation, generated and changed? Prior research tends to locate the principles of diversity dynamics in easily observable external environmental factors (Adner & Levinthal, 2001; Anderson & Tushman, 1990; Grodal et al., 2015; Suarez et al., 2015). However, the endogenous mechanisms that create and change diversity must be distinguished from the change process itself, which is driven by external factors (Endler, 1992; Fisher, 1930). In biological evolution, the internal factors of an organism play an important role as the engine of evolution (Wuketits, 1987). The processes of variation and retention that lead to genetic diversity dynamics occur independently of the adaptation and survival of individuals to their environment.

Technology evolve and develops by recombination through different paths of search. This process is driven by the decisions of heterogeneous actors. As a result of the recombination of technologies and the decision-making of actors, the diversity of technologies varies by increasing, stagnating, or decreasing (Carignani et al., 2019; Gao et al., 2013; Lin et al., 2021; Song et al., 2019). This study focuses on technological search and organizational routines of firms as internal factors for technological diversity dynamics. Furthermore, the impact of these internal factors on technological diversity dynamics is examined in the space of technological evolution, not as a whole, but for specific technological trajectories.

Technologies innovate by deepening existing technologies or by combining them with other technologies. Therefore, the search patterns for technological innovation can be classified into three categories: i) deepening existing technologies, ii) combining related technologies, or iii) new technologies without relevance before. More specifically, if there is a dominant design for a technology in an industry, the technology seeks incremental innovation based on the dominant design (Lin et al., 2021). In this case, innovation can be considered as a deepening of existing technologies (Anderson & Tushman, 1990; Suarez et al., 2015). On the other hand, when a dominant design has not emerged, or a next dominant design needs to be identified, technological competitions for dominance occurs (Anderson & Tushman, 1990; Suarez et al., 2015). New dominant designs are created by differentiating technologies from existing ones, introducing novel technological not previously present, or finding unique combinations of related technologies (Carignani et al., 2019; Suarez et al., 2015; Wagner & Rosen, 2014).

Meanwhile, unlike biological evolution, the evolution of technology has actors that directly generate diversity. Among these actors, this study examines the dynamics of diversity generated by firms, which are the intermediaries between technology and markets. Firms are heterogeneous (Hoopers & Madsen, 2008; Rumelt et al., 1994), and such heterogeneity causes firms to react and behave differently even in the same situations and conditions (Becker & Knudsen, 2017; Kirman, 1992). In evolutionary economics, firms are understood by organizational routines (e.g., Dosi et al., 2001; Feldman & Pentland, 2003; Winter, 1988). Routines are the inherent characteristics of a firm based on experience and are the origin of firm heterogeneity (Day, 1994; Dierickx & Cool, 1989). Firms engage in satisfying choice based on their unique routines (Nelson & Winter, 1982) and make decisions on different technological strategies and behaviors, which affect technological diversity.

In summary, technological search is a driver of diversity, directly generating and varying the diversity. Meanwhile, the patterns of technological search are the result of strategic decisions made by actors about which technologies to develop and how to develop them according to organizational routines. Therefore, organizational routines are micro-criteria for diversity dynamics in technology.



$$Y_{i,c} = M(X_i | R_c) \quad \textit{where,} \quad \begin{array}{ll} Y_{i,k} & \text{: Diversity Dynamics in Technology} \\ X_i & \text{: Patterns of Technological Search} \\ R_c & \text{: Organizational Routine of firm c} \end{array}$$

Figure 2-3. Conceptual framework of diversity dynamics in technology

Figure 2-3 is a mathematical representation of the technology diversity dynamics driven by technology search and organizational routines. Diversity dynamics are causally related to technological search and organizational routines. Through this conceptual framework, this study aims to understand the diversity dynamics of technology from the perspective of evolutionary economics. In addition, the proposed conceptual framework of diversity dynamics is examined in the evolutionary space of technology through an evolutionary phylogenetic approach.

Based on the theoretical background and methodological discussion in the literature review, this study takes the photovoltaic technology as the subject of empirical analysis. The following chapters provide an overview of photovoltaic technologies and background on the market and industry environments that influence technological diversity.

Chapter 3. Industry Review

3.1 Rationale for Case Selection: Challenges Facing the Photovoltaics

Reducing carbon emissions is essential for sustainable development. In particular, to limit global warming to 2°C or less, we need to approach net-zero before 2050. Photovoltaic technology is a mature technology that plays a key role in the global economy's transition to sustainability (Chowdhury et al., 2020; Paiano, 2015). There is general agreement that photovoltaic power capacity in the range of tens of terawatts (TW) is required to achieve sustainable development and "net zero 2050" (IEA, 2014, 2019, 2021; IRENA, 2019), and that the annual production of photovoltaic power should reach the terawatt scale in the future (Verlinden, 2020; Victoria et al., 2021). According to statistics from the International Renewable Energy Agency (IRENA), global installed capacity of photovoltaic power has increased more than 1,000-fold in the past two decades22. However, despite this growth, global photovoltaic power capacity remains at 848 gigawatts (GW) in 2021, with 132 GW newly added. Therefore, securing annual terawatt-scale production remains a challenging goal for photovoltaic technology.

The International Energy Agency (IEA) states that most of the carbon reduction aimed for by 2030 will come from technologies already on the market. However, by 2050, it will come from technologies that are currently in the demonstration or prototyping phase. As

[22] The global photovoltaic power capacity increases from approximately 809 megawatts (MW) in 2000 to 848,405 MW (848 GW) in 2021 (IRENA Renewable Energy Statistics database)

such, they emphasize that major innovation efforts must be made during this decade to bring these technologies to the market on time (IEA, 2021). Generally, as technology advances in stages, the previous generation of technology becomes obsolete. In the case of photovoltaic technology, however, materials, devices, and methods first developed decades ago are still in use today. Photovoltaic technologies are divided into generations based on market maturity, but in recent years, the convergence between them has led to advances in technology that make generational distinctions irrelevant. The situation implies that there is still plenty of room for innovation in photovoltaic technology and a wide range of options available.

To answer specific strategies and directions for technological innovation, it is necessary to assess the current position and situation in the dynamic development of the technology. This raises the following realistic questions about photovoltaic technology. Therefore, the following questions arise. What stage of development is photovoltaic technology currently in? How can the photovoltaic technologies existing in the market and laboratory be innovated?

This study explores solutions to these questions by empirically analyzing photovoltaic technology on the framework of endogenous dynamics in technological diversity. Technological diversity enhances existing technologies and boosts innovations by emerging totally different technologies (Anderson & Tushman, 1990; Carignani et al., 2019; Suarez et al., 2015). Accordingly, it is necessary to make efforts to improve technological diversity to achieve sustainable growth (Lin et al., 2021).

More specifically, an evolutionary phylogenetic tree is used to understand the evolutionary process of photovoltaic technology and verify the status of technological diversity. in addition, by deriving the principle for increasing technological diversity, the study suggests future directions for photovoltaic technology.

3.2 Introduction of Photovoltaic Technology

Photovoltaic power generation is the direct conversion of energy from solar light into electrical power. The basic unit is a photovoltaic cell (the same word as solar cell), which is a photoelectric conversion device, and the assembly of photovoltaic cells connected electrically is called a photovoltaic module. The electrical connection of photovoltaic modules and other components is called a photovoltaic power generation system (Chawla et al., 2020). The industry consists of the value chain related to photovoltaics, which is divided into three general parts: upstream, core, and downstream (Binz et al., 2017; Zhang & Gallagher, 2016). Upstream is the materials industry, which produces polysilicon, ingots, and wafers in the case of crystalline silicon photovoltaic cells. Photovoltaic cells and modules are produced in the core sector, and finally, the downstream sector installs and services systems by connecting them to power devices such as inverters. This study limits the scope of technology analysis to the core sector, focusing on photovoltaic cells and modules.

The fundamental operating principle of photovoltaic power generation is the photoelectric effect, which converts light into electricity through the p-n (or p-i-n) semiconducting junction of a photovoltaic cell. When light is irradiated, electrons and holes are created inside the device, and the generated charges are transferred to the n-type and p-type semiconductors, respectively, resulting in a potential difference, that is photovoltaic power. Therefore, conversion efficiency, which is how much light can be turned into electricity, is a performance indicator of photovoltaic technology, which generally refers to the progress of photovoltaic cell technology. It is also directly linked to the unit cost of production, with a 1% increase in the conversion efficiency of a photovoltaic cell resulting in a 5-7% decrease in total cost per Watt (IEA, 2014).

Table 3-1. Photovoltaic technology classification

Generation	Market Maturity	Technology	Detailed technology
First	Fully commercial	Crystalline silicon	Mono-crystalline silicon photovoltaic cells Multi-crystalline silicon photovoltaic cells Ribbon or sheet type crystalline silicon photovoltaic cells
Second	Deployed on a commercial scale, but low volume	Thin film compound	Amorphous silicon thin film photovoltaic cells CdTe thin film photovoltaic cells Coppor-Indium-Selenide (CIS) or CIGS photovoltaic cells
Third	Under demonstration	Emerging	Organic photovoltaic cells Dye-sensitized photovoltaic cells (DSSC) Perovskite photovoltaic cells Quantum dot photovoltaic cells Etc.

Photovoltaic cell technology is broadly classified by semiconducting material into crystalline silicon photovoltaic cells, compound thin-film photovoltaic cells, and emerging photovoltaic cells that utilize new materials such as organic or dye-sensitized materials. Photovoltaic technology is generally classified into first-, second-, and third-generations, depending on semiconducting materials and market maturity. **Table 3-1** shows the classification of photovoltaic technologies by generation (EPIA, 2014; Lacerda & Van Den Bergh, 2016; Taylor et al., 2016).

First-generation photovoltaic cells currently account for more than 90% of the market. Since the 1950s, the photoconversion efficiency of crystalline silicon photovoltaic cells has steadily increased, reaching lab-scaled efficiencies of 26-27%. First-generation technology has many benefits, including years of accumulated technological know-how and durability for a lifetime of more than 25 years. However, the physical properties of silicon materials limit the improvement of conversion efficiency, and the amount of silicon used accounts for a high proportion of the production cost.

Second-generation photovoltaic cells are based on the deposition technology of a light-absorbing layer with several micro-meters (μm) thick on a glass, metal, or plastic substrate. Materials used for the light-absorbing layer include amorphous silicon, cadmium telluride (CdTe), copper-indium-gallium-diselenide (CIGS) and so on. Second-generation photovoltaic cells emerged as an alternative to first-generation photovoltaic cells due to substrate freedom and lower material usage. However, as the price of polysilicon has stabilized, the advantage of production cost has disappeared, and the competitiveness has deteriorated significantly due to difficulties in large area through uniform deposition. Recently, to improve the low light conversion efficiency, structural changes have been attempted by stacking thin films such as tandem and triple layers.

Third-generation photovoltaic cells are the so-called next-generation photovoltaic cell technology, which is based on new materials, processes, and structures, ranging from dye-sensitized photovoltaic cells that use the principle of photosynthesis to perovskite photovoltaic cells[23] that have recently attracted attention. They are derived from attempts to improve the economics, applicability, and availability of raw materials of first- and second-generation photovoltaic cells. While most of these technologies are still in laboratory and require a long time to be commercialized, perovskite photovoltaic cells are attempting to enter the market by integrating with conventional photovoltaic cells.

Figure 3-1 represents the technology trajectory of photovoltaics with the highest efficiency of laboratory-scaled photovoltaic cells as reported to the National Renewable Energy Laboratory (NREL), part of the U.S. Department of Energy[24]. There are a total of 347 records for terrestrial photovoltaic cells (excluding groups 3-5 and concentrating types) compiled from 1976 to 2020 (NREL, 2022). The number of records for the highest efficiency is on rise, indicating that photovoltaic technology has been continuously

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[23] Perovskite is the name given to the crystalline structure, which has a chemical composition of ABO_3 with two cations and one anion in a ratio of 1:1:3. Perovskite, which is used as a light-absorbing layer in solar cells, has a crystal structure of AMX_3, which is mainly a mixture of organic and inorganic materials. A is an organic cation such as methylammonium or formamidine, M is a metal cation such as lead (Pb), and X is a halogen anion such as iodide (I^-) or bromide (Br^-).

[24] Dosi (1982, 1988) described the process of technological innovation through the concepts of trajectories and paradigms. Trajectories are mappings of the dynamics of a technology, and previous studies have diagrammed technological trajectories by linking products with the highest technology level with a line (Christensen and Bower, 1996; Schaller, 1997).

advancing in quantity. In addition, it was composed of first-generation (blue) and second-generation (red) technology groups before the 1990s. However, third-generation technologies (gray and green) are gradually added and their proportion increases. From the **Figure 3-1**, it is intuitively clear that the pace of development of photovoltaic technology has accelerated over time, and various technologies have been developed.

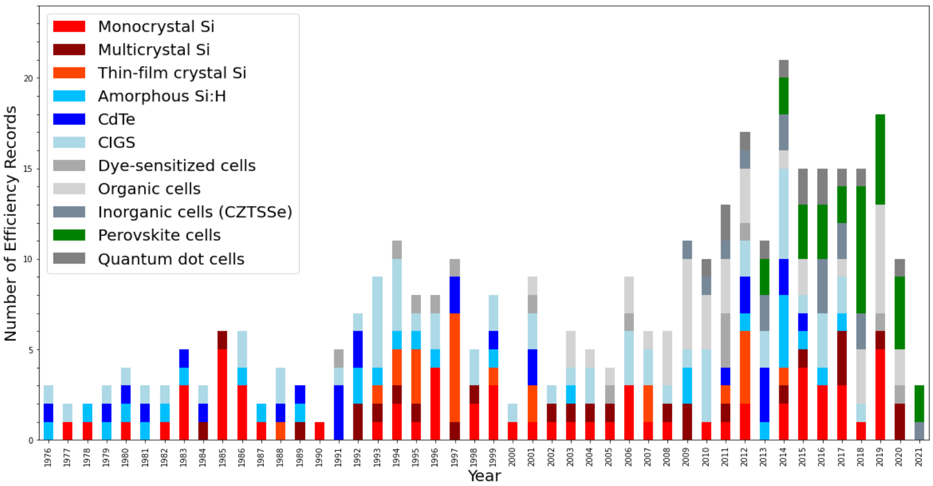

Figure 3-1. Number of lab-scale best photovoltaic efficiency records

(Author's reproduction based on NREL (2022))

As described so far, photovoltaic technologies are categorized into three groups based on the market maturity. However, recent trends show a convergence and mutual development without distinction of technologies. Therefore, a specific strategy for their future development based on scientific and quantitative evidence is needed for more efficient and effective technology development. This study approaches this need by identifying detailed technology trajectories, diagnosing the current state of photovoltaic technology, and suggesting future directions. The following section provides a review of the external changes surrounding photovoltaic technology, that is the changing market and industry landscape.

3.3 Environmental Changes for Photovoltaic Technology

Once a niche industry for powering remote locations such as space satellites, the photovoltaic industry has developed rapidly as awareness of the environmental impact and economic volatility of fossil fuel reliance increased (Bagnall & Boreland, 2008). Particularly, in the late 1990s, demand-pull policies, such as feed-in tariffs implemented in several countries, starting with Germany, Japan, and the United States, explosively expanded the photovoltaic market, which had remained for remote power generation, to the existing on-grid market (Mints, 2012). Consequently, the photovoltaic industry has grown rapidly since the 2000s, with an average annual growth rate of approximately 40% (Bagnall & Boreland, 2008).

Such government-led industrial development has led to increased investment in research and development (R&D), resulting in increased technological diversity and innovation25. This is because the policy goal of most countries to foster the photovoltaic industry is not simply to reduce carbon emissions by supplying eco-friendly energy but also

[25] Various technological innovations have been generated, such as reducing the use of materials in wafers and electrodes of silicon solar cells, developing high-efficiency cell structures and technologies like selective emitter formation, or pointed rear contact, and applying new materials such as perovskite. As a result, the innovations have improved conversion efficiency and reduced manufacturing cost (Gan & Li, 2015; Green, 2019; Green et al., 2014).

to induce innovation in new and renewable energy to lead the country's economy. However, it is also pointed out that demand-pull policies and rushed market formation have led to the lock-in of photovoltaic technologies and hindered radical innovation through various technological advances (Che et al., 2022; J. Lee et al., 2022; Nemet, 2009; Schmidt et al., 2016). The dynamics of a given external environment can either inspire innovation or create an imbalance, making it a "double-edged sword" for technology and innovation.

The dynamics in the photovoltaic industry and market environment during the analysis period are summarized in **Table 3-2** based in the literature review (Algieri et al., 2011; Gan & Li, 2015; Green, 2005, 2019a, 2019b; Hopkins & Li, 2016; Kapoor & Furr, 2015; Mints, 2012; Wang, 2012).

Table 3-2. Brief description of environmental dynamics for photovoltaic technology

	Year	Changes in the market and industry
1	2000 - 2004	Execution of demand-pull policies in Europe, led by Germany and Japan Rapid industrialization through government-led market creation Promote the production of crystalline silicon photovoltaic cells Rise of Al-BSF photovoltaic cells as a market dominant design Entry barriers lowered due to the spread of turn-key equipment
2	2004 - 2008	European Feed-in-Tariff expands globally Market over-heated Polysilicon shortage and price surge ($30/kg → $400/kg) Commercialization of thin film photovoltaic cells
3	2008 - 2013	Intensification of competition Aggressive scale expansion of Chinese firms (Share of global production capacity 1.1% (2000) → 28.4% (2008)) Demand contraction due to reduction and elimination of subsidies caused by global crisis Oversupply and a sharp drop in prices Both process and product innovation on crystalline silicon photovoltaic cells Industrial restructuring Trade dispute between western (EU, US) and China Introduction of perovskite as the material of photovoltaic cells
4	2013 - Current	Transition of market dominant design to PERC cell Rapid pace of technological innovation Expansion of innovation scope and active technology convergence Enhanced market competitiveness as a source of energy (2%/year improvement in conversion efficiency and over 15%/year reduction in manufacturing costs through 2010-2020)

Period 1 is when the industrialization of photovoltaics began in earnest. The main issue was the mass production of the standard technology which is the crystalline silicon photovoltaic cells developed in the 1960s and 1970s (Green et al., 2005; Kazmerski, 2006; Wand & Leuthold, 2011; Wilson et al., 2020). The aluminum back surface field (Al-BSF) photovoltaic cell, based on a P-type silicon wafer, was selected as the dominant design for the industry. As technologies converged, the turn-key equipment industry developed rapidly, easing technical barriers to entry. In addition, basic materials (e.g., Ethylene Vinyl Acetate) and structural technologies to improve the durability and reliability of photovoltaic modules were also rapidly applied in line with mass production.

Meanwhile, in **Period 2**, the raw material instability caused by the polysilicon supply crisis of 2004 has led to several technological advancements through awareness of the material dependence of photovoltaic technology. During this period, wafer thickness was reduced from 300 μm to 180 μm to save the use of silicon materials, and ultra-thin photovoltaic cells such as applying 50 μm or less wafers were also developed (Green, 2019a). On the other hand, as an alternative to crystalline silicon photovoltaic cells, second- and third-generation technologies actively developed, and particularly, it led to an increase in the market share of thin-film photovoltaics from 5.5% in 2004 to 11.4% in 2007 and 13.4% in 2010 (Gan & Li, 2015; Kirkegaard et al., 2010; Price et al., 2010).

Various technological developments prompted by the environmental crisis led to important patents that marked the history of photovoltaics. The first was the back contact solar cell (Richard M. Swanson, US 6664838), which moved all the electrodes on the front to the back. This notable structured crystalline silicon photovoltaic cell succeeded in placing the metal contacts to the rear by controlling the contact resistance with the doping concentration and drew an improvement on light absorption. A patent (US 6953862) on a thin film photovoltaic cell manufacturing method using hydrogen plasma treatment filed by Sharp corporation increased the conversion efficiency of amorphous silicon thin film photovoltaic cells, and First Solar became the first company to achieve $1/watt in 2008 based on a patent (US 7618236) on a manufacturing method for CdTe thin film photovoltaic cells filed in 2004. In addition, patents on flexible photovoltaic cell manufacturing process based on organic materials (Kaneka technology, US 6819163) and multi-junction photovoltaic cell patent (Spectrolab, US 6730118) have contributed to the development of emerging photovoltaic cells as an alternative to silicon-based photovoltaic cells.

Period 3 marks the beginning of a period of intense competition and recession in the photovoltaic industry. The global crisis that began in the United States in 2008 dealt a heavy blow to the photovoltaic industry. As in each country in Europe, the world's largest demand source, subsidies were greatly reduced, and the market shrank sharply. In addition, with the Chinese government's strong financial support, Chinese firms, encouraged by the past photovoltaic boom, aggressively expanded their scale against the supply and demand situation in the market[26]. Ultimately, the photovoltaic industry faced an oversupply and falling prices. Uncompetitive firms were forced to exit, and the industry was reorganized through a shake-out.

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[26] China emerged as the largest producer, accounting for 28.4 percent of global production in 2008, up from just 1.1 percent in 2000.

In this competitive situation, the first generation of photovoltaic technologies sought to replace the Al-BSF photovoltaic cells, which have become more common. Technologies were developed to commercialized photovoltaic cell structures implemented in the laboratory, such as Passivated emitter and real Contact (PERC) cells, Interdigitated Back Contact (IBC) cells, Silicon Hetero Junction (SHJ) cells (Khatibi et al., 2019). For this purpose, the existing p-type silicon substrates diversified to n-type wafers, and elemental technologies such as selective emitter formation, backside localized junction structure, and new electrode formation technology through plating or laser transfer developed for high efficiency (Green, 2019b).

Moreover, to improve the physical limitations of materials and secure light absorption across the entire wavelength range, tandem photovoltaic cells widely studied. Researchers had various attempts to integrate first-generation photovoltaic cell technology with second- and third-generation one, such as using crystalline silicon photovoltaic cells as the bottom cell and thin films such as CIGS, or perovskite materials as the top cell (Green et al., 2014; Tonui et al., 2018).

For third-generation technologies, investment weakened during the recession, and the scale of R&D was somewhat reduced. However, since the publication of a 3.8 percent photovoltaic cell with an organic-inorganic composite perovskite as the light-absorbing layer in 2009 (Kojima et al., 2009), the number of related studies increased rapidly. Furthermore, novel material technologies such as non-fullerene organic molecules, nanocrystals, and quantum dots applied to photovoltaic technology. Meanwhile, module technology developed to expand applications, and innovative concepts such as colored, flexible, and stretchable introduced to develop niche markets outside of the existing residential and utility markets, such as wearable devices and car roofs (Sharma et al., 2015).

In **Period 4**, photovoltaics leaps again. Throughout the recession, first-generation technologies continued to aggressively pursue product and process innovation. Silicon wafers became thinner to reduce material usage, while their size increased from 125mm in 2010 to 166mm or 210mm to increase light absorption. PERC replaced Al-BSF photovoltaic cells to become the new dominant design in the market (Baliozian et al., 2020; Chawla et al., 2020; Wilson et al., 2020). From 2010 to 2020, the light conversion efficiency of silicon photovoltaic cells improved by 2% per year, while manufacturing costs decreased by more than 15% per year on average, making them market competitive (Wilson et al., 2020). These advances in photovoltaic technology have enabled photovoltaics as an energy source to begin to compete with conventional fuels. Variations in photovoltaic cell structure, wafer thickness and size affect the design and assembly of photovoltaic modules and potentially module reliability. Hence, progress in photovoltaic cell technology has led to improvements in module technology. In addition, the emergence of TOPCon (Tunnel Oxide Passivated contact) photovoltaic cells triggered the development of bifacial modules, and the progress of module technology has been further accelerated as the lifecycle and recycling of photovoltaic modules has become an issue under the banner of sustainability (Frischknecht et al., 2015; Wang et al., 2022; Wilson et al., 2020).

Up to this point, this study has been confirmed that photovoltaic technology has developed in interaction with the external environment. Based on industry life cycle theory[27], it is observed that the photovoltaic industry is currently somewhere along the path from maturity to either decline or renewal[28]. The maturity phase of the industry focuses on optimization and improvement of existing technologies based on dominant designs, and efficiency is maximized. This is followed by the decline phase, where technologies are standardized, firms consolidate, and innovation tends to slow down. However, when new technologies emerge to replace old ones, innovation is again spurred, and the stage may progress to a renewal phase (Markard, 2020).

The photovoltaic industry has experienced dramatic growth over the past two decades, as well as dynamic conditions such as intense competition, cost pressures, and the global crisis. Along the way, lots of companies have entered and exited, and grid parity[29] has been achieved through continuous product and process innovations. Whether the photovoltaic industry will enter a declining phase or a renewal phase, and whether photovoltaics will achieve the challenging goals on a sustainable energy system described above, depends on

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[27] The model formalizes the dynamic pattern of firm entry and exit at the industry level (Abernathy & Utterback, 1978). In the initial stage, existing firms in the industry enter the new market with simple designs (Klepper, 1996), and many new firms, seeing a large market opportunity, enter, develop a variety of products, and drive the growth of the industry. A dominant design then emerges, production is standardized, the number of firms remains constant, and more firms exit than enter. Eventually, industry growth stagnates, unsuccessful firms leave the market, and the industry declines (Klepper, 1997; Klepper & Graddy, 1990; Klepper & Simons, 2005). The four stages of industry development are generally categorized as introduction, growth, maturity, and decline, but different scholars simplify or refine them further, with the disadvantage that the stage of industry development varies depending on the time period analyzed. Furthermore, while a large number of industries develop in a regular manner, there are also industries that deviate from the typical pattern, which is a limitation of the ILC theory.

[28] The industry life cycle is one of the major research areas and requires a separate study for accurate analysis. Therefore, the opinion of this study for photovoltaic industry has limitations because it is based on the comprehensive context provided by IRENA (2017, 2019) and IEA (2022).

[29] The level of cost that are competitive with the cost of producing electricity from conventional fossil generation.

further technological innovation.

To find clues to specific innovation directions, this study aims to derive the endogenous mechanism of diversity dynamics in technology based on an understanding of technological evolution. As a first step, the following chapter examines the evolutionary phylogenetic tree of photovoltaic technology and the diversity dynamics in the evolutionary process.

Chapter 4. Diversity Dynamics through Evolutionary Phylogenetic Approach

4.1 Quantitative Measure of Diversity on Technological Trajectory

Technologies develop through detailed developmental trajectories formed by sub-technologies (Dosi, 1982; Dosi & Nelson, 2010). Over time, technology trajectories may persist, diverge into new and distinct trajectories (Levinthal, 1998), or disappear (Tellis & Crawford, 1981). In doing so, trajectories create a technological space where technology evolves. However, previous studies have comprehensively analyzed technological diversity at the level of broad categories such as industry (Anderson & Tushman, 2018; Gao et al., 2013; Lin et al., 2021; Utterback & Abernathy, 1975). Thus, the evolutionary space and detailed trajectories of technological diversity have been less discussed. It is possible to make the error of generalization when measuring technological diversity from an integrated perspective without considering the technological trajectories, as in the example of mobile industry presented in **Section 2.3**.

This study identifies specific developmental trajectories of technologies from an evolutionary point of view and depicts the space they occupy in a evolutionary phylogenetic tree (J.-D. Lee et al., 2022). The evolutionary phylogenetic approach presented in this study is a novel and effective methodology that can explain the phenomenon of technological development by evolutionary analogy. Technology diversity is measured quantitatively by considering detailed trajectories and utilizing information described in the phylogenetic tree.

Diversity is essentially a property of all systems whose elements can be classified into categories (Leonard & Jones, 1989). The basic properties of ‘disparity’, ‘variety’, and ‘balance’ combine to form diversity (Stirling, 1994). First, disparity is a fundamental characteristic for categorization by defining and classifying elements. Without disparity, that is, if all elements are the same, diversity itself cannot be defined. Therefore, disparity represents ‘how different the categories of the system are from each other’ (May, 1990). Meanwhile, variety is the number of categories into which a population can be divided, meaning ‘how many different kinds of categories exist’, and balance is the frequency distribution of each category, meaning ‘how much of each kind of category is present’. Ceteris paribus, the greater the disparity, the more variety, or the more even the balance, the greater the diversity.

Scholars who understand the important role of diversity in technological innovation quantitatively measure numerical changes in patents (Gao et al., 2013), firms (Cohendet et al., 1992; Suarez et al., 2015), and products (Kauffman, 1993; Saviotti & Mani, 1995; Utterback & Abernathy, 1975). This approach quantifies variety characteristics of diversity according to a specific disparity criterion. However, diversity in technology cannot be judged solely quantitatively.

As an example, suppose there are two technologies, technology A and B, that have the same number of patents and IPC code types (**Figure 4-1)**. Each type of IPC codes represents a technological difference as a proxy for detailed technology. For technology A, the distribution of patents classified by IPC codes is uniform, while for technology B, most patents exist in some specific IPC codes. When quantitatively measuring diversity with respect to variance and disparity in this example, technologies A and B are equivalent. However, in terms of the potential for generating various technologies and with respect to balance, Technology A is more diverse than Technology B (Lin et al, 2021).

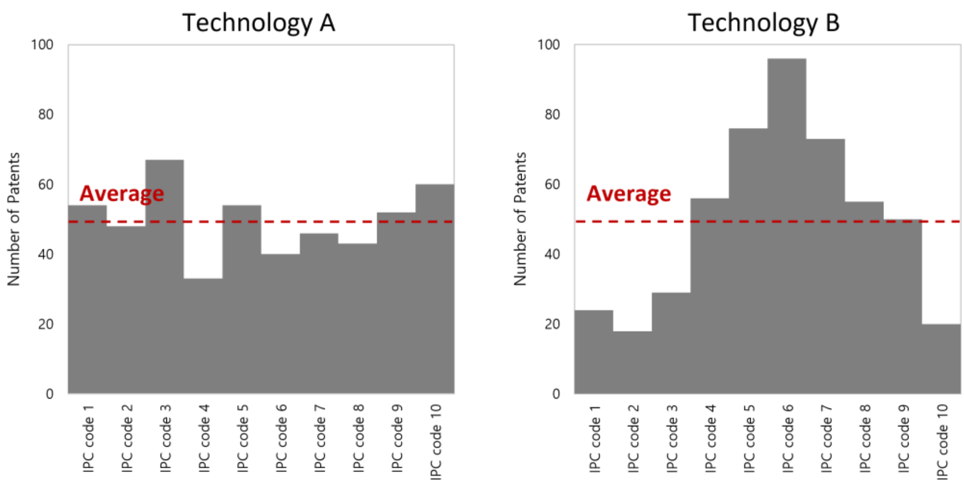


Figure 4-1. Uniform and skewed distribution of IPC code in technologies

Information entropy allows to account for distributional distinction in addition to quantitative differences in technological diversity (Frenken, 2006; Frenken & Nuvolari, 2002; Frenken et al., 1999; Saviotti, 1988; Zhang, Qian, et al., 2017). Based on the information theory, information entropy refers to the expected value in a certain system[30].

[30] Entropy was originally developed in thermodynamics in the 19th century to describe randomly moving

In other words, entropy is the level of surprise, disorder, and diversity (Frenken, 2006), and is expressed in the form of **Equation (4-1)** (Shannon, 1948).

$$H(Z) = E_{X\sim Z}[I(x)] = \sum_{i=1}^{N} -P(x_i)(log\,P(x_i)) \qquad \text{Eq. (4-1)}$$

Z denotes the specific probability distribution and $I(x)$ is the information of event x. Additionally, $E_{X\sim Z}[I(x)]$ represents the expected information value of all events constituting Z. The larger the number of events and the more uniform the distribution, the greater the entropy value (Shannon, 1948). In other words, if the diversity of an event increases and adds uncertainty to the system, the amount of information grows, leading to a rise in entropy (Frenken (2006)).

As a measure of technological diversity, entropy quantifies the distribution of technological elements in the space of technology. When randomness increases due to large and complex diversity, the probability distribution is flat, and the maximum value of entropy is derived. On the other hand, if the probability distribution is skewed, the entropy decreases due to the dominance of a particular design (technology), and the minimum value of entropy, that is zero, is a situation where only one design exists without diversity.

As an example of prior research, Frenken et al. (1999) measured the diversity of helicopters, motorcycles, and microcomputer technologies using entropy and maximum

particles but was introduced into information theory by Shannon (1984) and has since been used in a variety of contexts in the social sciences.

likelihood procedures to study the occurrence of niches. Zhang, Qian et al. (2017) measured the entropy of each patent attribute, identified attributes with high and low diversity, and analyzed the weight of patent attributes. Lin et al. (2021) derived the change in technology diversity by measuring the entropy of patent applications by year in a technology life cycle study, and identified whether the technology was in the maturity stage or the decline stage.

To sum up, this study constructs the evolutionary phylogenetic tree of technology and then measures the entropy of technological diversity in each evolutionary lineage. This approach allows to observe the dynamics of technological dynamics considering technology space and trajectories. An in-depth study of diversity dynamics in technology along detailed technological trajectories will lead to more specific and practical suggestions for generating innovation.

4.2 Methodology

4.2.1 Data

Granted photovoltaic patents were collected from the United States Patent and Trademark Office (USPTO) database for empirical research. Firstly, among patents granted from 2000 to 2020, patents are selected by specific keywords related to photovoltaics in abstract. In addition, after classifying the 12 Main-group level International Patent Classification (IPC) codes related to photovoltaic technology, the IPC codes possessed by each patent were analyzed. The search queries and methods are summarized in **Table 4-1** (J. Lee et al., 2022; Taylor et al., 2016; Wu & Mathews, 2012), and a total 9,663 patents were initially extracted.

Table 4-1. Data search method

Period		2000~2020
Keywords in Abstract		"solar*" OR "photovoltaic*" OR "solarbatter*" OR "photo-voltaic*"
IPC Code (Main Group)	Common technology	H01L21, H01L31, E04D13
	Crystal Si (1st Generation)	H01L27, H02N6, C30B15, C30B29, C30B28
	Compound Thin Film (2nd Generation)	C23C14, C23C16
	Emerging Others (3rd Generation)	H01G9, H0lL51

* Source: Author's reconstruction based on previous studies (J. Lee et al., 2022; Taylor et al., 2016; Wu and Mathews, 2012) and interviews with photovoltaic technology experts

However, when the primary extracted patent data is organized by filing date, the number of patents drops dramatically after 2019. This is because it takes about two years for a patent to be granted from the date of filing (USPTO, 2020). Therefore, after 2019, when the number of patents sharply decreased, was excluded from the analysis. As a result, this study used 8,081 granted photovoltaic patents filed between 2000 and 2018.

This study used IPC codes of patents a proxy of the detailed technology. Each of 8,081 patents held 12 Main-group IPC codes shown in **Table 4-1**, which are further subdivided into Sub-group IPC codes (e.g., H01L 21 (Main-group): H01L 21 (Main-group), H01L 21/285 (Sub-group IPC)). Finally, 319 Sub-group IPC codes derived from 8,081 patents were analyzed in this study.

4.2.2 Construction of Technology Evolutionary Phylogenetic Tree

This section describes the methodology for constructing the evolutionary phylogenetic tree of technology using patent data. Despite some incompleteness, patent data are commonly used in the study of technology and innovation from an evolutionary perspective, because they provide the most direct information about technologies and their relationship to each other (Martinelli & Nomaler, 2014)[31]. This study refers to algorithms for constructing the evolutionary phylogenetic tree of technology developed by J.-D. Lee et al. (2022). They introduced a generalized algorithm that can be applied to technology data as well as products.

[31] Patent data contains citation information, and many studies have utilized citations to define relationships between patents. However, this approach assumes that patent citations reflect meaningful connections between technologies, indicating influence or prior art (Funk & Owen-Smith, 2017). The citations of prior patents are sometimes strategically selected during the patent application process, and there is a time lag between filing and citation. Therefore, intentionally omitted patents or delayed citations cannot accurately represent the relationship between technologies or the process of technological development. This study complements the limitations of previous studies based on patent citations by connecting ancestors and descendants through a scientific approach based on network theory within the information of each patent.

First, derive technology taxa as nodes for an evolutionary phylogenetic tree. Evolutionary variation does not accumulate in an individual, but rather within homogeneous populations, and this drives frequency-dependent evolution (Kardong, 2008). Similarly, in technological evolution, large trajectories of technological change can be identified by deriving technology taxa - groups of technologies that are technologically homogeneous - and linking the evolutionary relationships they form with their descendants (J. -D. Lee et al., 2022). Therefore, technology taxa should be organized by considering the homogeneity of technology gene units for technological recombination. In this study, to consider this point, we define the gene of a technology as a unit of IPC code and derive a technology taxon as a group of patents with technological homogeneity in a specific year. We utilize the cosine similarity of IPC codes to define the links in the patent network, so that it can reflect the similarity of technology genes. A group of patents is identified by constructing a patent network by filing time. In defining the links in the patent network, the cosine similarity of the IPC codes was utilized to reflect the similarity of the technology genes. Finally, apply community detection methodology on the patent network to derive homogeneous patent groups and define them as technology taxa (Despalatović et al., 2014; Fortunato, 2010; J.-D. Lee et al., 2022; Youngblood et al., 2021). The community detection algorithm is designed to organize communities (technology taxa) in such a way that the number of links between nodes within the same community is higher than the expected value of the link values formed with nodes belonging to other communities. In other words, this algorithm can derive groups with higher similarity of technology genes. For this process, one patent is converted into a vector as presented in **Equation (4-2)**.

$$Z_{it} = Patent_{it} \qquad \text{Eq. (4-2)}$$

$$x_k = 1 \; if \; Z_{it} \; has \; IPC \; code_k; \; otherwise \; 0$$

$$If \; Z_{it} \; has \; IPC \; code_1, IPC \; code_3, IPC \; code_m$$

$$Z_{it} = [x_1, x_2, x_3, \ldots, x_m, \ldots] = [1,0,1, \ldots ,1]$$

Z_{it} denotes a patent i filed at time t and is a vector representing the value of 1 if a patent i has the specific IPC code and 0 otherwise. A patent has one or more IPC codes that refer to the technology class covered by that patent. The larger the number of IPC codes held by a group of patents, the higher the level of technological diversity (Gao et al., 2013). To use a biological analogy, a patent and an IPC code are regarded as entities and genes, respectively. When a technology is represented as a patent, this enhances diversity by increasing the number of IPC codes as genes. This study uses 319 sub-group IPC codes as a means of representing technological characteristics of the patent. Hence one patent is converted into a 319-dimensional vector composed of 0 or 1.

Since patents are converted into vectors, which are empirical units, the similarity between different patents can be measured, and then a patent network can be constructed based on it (J.-D. Lee et al., 2022). Therefore, a patent network ($G_t(V, E)$) for patents filed at a certain time is built as shown in **Equation (4-3)**.

$$G_t(V, E) \qquad \text{Eq. (4-3)}$$
$$V = \{Z_{1t}, Z_{2t}, Z_{3t}, \dots\}$$
$$E = \{e_{ij} | 1 \; if \; cosine \; similarity(Z_{it}, Z_{jt}) \geq thershold; \; otherwise \; 0\}$$

The patent network $G_t(V, E)$ at time t has a set of nodes, V, representing patents granted in year t, and forms links if the cosine similarity between the patents is higher than a certain threshold. Specifically, the link of the patent network is formed according to the similarity of IPC codes contained in each patent. This study set the threshold at 0.5, so let patents connect links when IPC code similarity of more than half.

$$Community \; Detection\big(G_t(V, E)\big) = \{C_{1t}, C_{2t}, C_{3t}, , \dots, C_{jt}, \dots\} \qquad \text{Eq. (4-4)}$$

All the nodes constituting the photovoltaic patent network in every year can be classified as a community, a group of homogeneous nodes (Clauset et al., 2004; Newman, 2018). In this study, the patent community C_{jt}, derived by applying the community detection algorithm to the patent network of each year, is defined as a technology taxon existing at time t (**Equation (4-4)**). Technology taxon is similar to the concept of species in biology. Because biological crossover occurs only within a species, technological recombination occurs more naturally within the same taxon, which has a certain level of technological homogeneity (J.-D. Lee et al., 2022). To analyze the technological diversity for this study, taxa with a certain number of patents are required. Therefore, 108 technology taxa containing 5 or more patents are identified and applied as nodes in the photovoltaic technology phylogenetic tree.

The evolutionary phylogenetic tree of technology is a tree-type network with nodes for the technology taxa of each year and links for the ancestor-descendant relationships between technology taxa. To link the ancestor-descendant relationships, the technology taxa are converted into weighted vectors using the Term Frequency – Inverse Document Frequency (TF-IDF) method (J.-D. Lee et al., 2022; Zhang et al., 2014). TF-IDF method converts a document consisting of multiple terms into a weighted vector. The weight of a term is derived by multiplying the number of occurrences of the term in the document by the reciprocal of the number of documents in which the term appears. Hence terms that appear frequently in a specific document but not in others have a high weight in the document vector. That is, the higher the weight in the TF-IDF vector of a certain document, the more representative the term is of that document. Since a technology taxon in this analysis is a set of patents composed of IPC codes, taxa and IPC codes correspond to documents and terms, respectively. The formular for converting a technology taxon into a weighted vector by TF-IDF method is shown in **Equation (4-5)**.

$$F_{kjt} = Number\ of\ IPC\ code_k\ in\ C_{jt} \qquad \text{Eq. (4-5)}$$

$$IF_{kt} = log\ (\frac{Total\ Number\ of\ Taxa\ in\ t}{1 + Number\ of\ Taxa\ which\ have\ IPC\ code_k\ in\ t})$$

$$w_{kjt} = F_{kjt} \times IF_{kt}$$

$$C_{jt} = [w_{0jt}, w_{1jt}, w_{2jt}, \dots]$$

F_{kjt} is the number of $IPC\ code_k$ present in a certain technology taxon C_{jt}, while IF_{kt} is the logarithm value of the reciprocal of the ratio of technology taxa containing at least one $IPC\ code_k$ in the total number of taxa existing at time t. these two values are multiplied to derive the weight w_{kjt} of $IPC\ code_k$ which consist of the technology taxon C_{jt}, and convert C_{jt} to a weighted vector.

Using **Equation (4-5)**, the technology taxa existing at every time are converted into weighted vectors. The weighted vector value of the technology taxon is used to measure the similarity between technology taxa, and the ancestor-descendant relationship between taxa is derived using this.

$$t(Descendant) > t-1(Ancestor) \qquad \text{Eq. (4-6)}$$

$$\Phi_i = \underset{C_{jt-1}}{argmax}\{Cosine\ Similarity(C_{it}, C_{jt-1})\}$$

$$Then,\ \Phi_i\ is\ ancestor\ of\ C_{it}$$

As expressed in **Equation (4-6)**, for a certain taxon at time t, an ancestor is the taxon of the highest cosine similarity among all taxa at time t-1, based on the principle of evolution (Chavalarias & Cointet, 2013; J.-D. Lee et al., 2022). After defining ancestor-descendant relationships, the evolutionary phylogenetic tree of photovoltaic technology is eventually constructed as a form of tree-type network with nodes for 108 taxa and links for ancestral relationship.

Table 4-2 summarizes the operational definitions of the elements used to construct the evolutionary phylogenetic tree discussed in this section. Through the phylogenetic tree, we observed the technology trajectories and evolutionary landscapes in photovoltaic technology.

Table 4-2. Operational definitions for phylogenetic tree for photovoltaic technology

Terminology	Operational definition	Description
Technology	Z_{it}	Patent
Technology gene	$IPC\ code_k$	IPC Code
Technology vector	$x_k = 1\ if\ Z_{it}\ has\ IPC\ Code_k;\ otherwise\ 0$ $If\ Z_{it}\ has\ IPC\ Code_1, IPC\ Code_3, IPC\ Code_m$ $Z_{it} = [x_1, x_2, x_3, \dots, x_m, \dots] = [1,0,1, \dots, 1, \dots]$	Vector representation of the patent
Technology taxon (C_{jt})	$G_t(V, E)$ $V = \{Z_{1t}, Z_{2t}, Z_{3t}, \dots\}$ $E = \{e_{ij} \| 1\ if\ cosine\ similarity(Z_{it}, Z_{jt}) \geq thershold;\ otherwise\ 0\}$ $Community\ Detection(G_t(V, E)) = \{C_{1t}, C_{2t}, C_{3t},, \dots, C_{jt}, \dots\}$	Patent community with more than threshold level of homogeneity in t
Technology taxon vector	$F_{kjt} = Number\ of\ IPC\ Code_k\ in\ C_{jt}$ $IF_{kt} = \log\left(\frac{Total\ Number\ of\ Taxa\ in\ t}{1 + Number\ of\ Taxa\ which\ have\ IPC\ Code_k\ in\ t}\right)$ $w_{kjt} = F_{kjt} \times IF_{kt}$ $C_{jt} = [w_{0jt}, w_{1jt}, w_{2jt}, \dots]$	Vector representation of the technology taxon
Ancestor $(\Phi_i)$and descendant (C_i^t)	$t(Descendant) > t-1(Ancestor)$ $\Phi_i = \underset{C_{jt-1}}{argmax}\{Cosine\ Similarity(C_{it}, C_{jt-1})\}$ $Then,\ \Phi_i\ is\ ancestor\ of\ C_{it}$	Relationship with the highest cosine similarity between adjacent period taxa
Phylogenetic tree of Technology	Node = Technology taxon Link = ancestor and descendant relationship between taxa in adjacent period	Tree representing evolutionary relationships between taxa in chronological order

4.2.3 Operational Definition of Diversity

Considering a systemic aspect from an evolutionary perspective, technological diversity in this study is defined as the diversity of a given taxon in a phylogenetic tree, which is measured by the information entropy of IPC codes. In more detail, the taxa comprising the phylogenetic tree are a set of technologically homogeneous patents, each of which has multiple IPC codes related to photovoltaic technology. In this study, we measure the entropy of a taxon based on these IPC code configurations, which we define as the diversity of the taxon. Thus, the technological diversity of a technology taxon can be expressed as **Equation (4-7).**

$$Technological\ Diversity(C_{jt}) = \sum_{k=1}^{n} -p_{kjt} ln(p_{kjt}) \qquad \text{Eq. (4-7)}$$

p_{kjt} denotes the probability of emergence of $IPC\ code_k$ present in taxon C_{jt}, and is derived by dividing the number of all IPC codes constituting C_{jt} by the frequency of emergence of $IPC\ code_k$. The diversity of a technology taxon has a higher value when the number of IPC codes is larger and the distribution is more uniform, and conversely, a lower value when the distribution is skewed toward specific IPC codes.

In following section, the evolutionary phylogenetic tree of photovoltaic technology is constructed, and the diversity dynamics is examined on it. The relevance of the evolutionary phylogenetic tree is verified by observing whether the constructed photovoltaic technology phylogenetic tree depicts the actual technology development.

4.3 Evolution and Diversity Dynamics of Photovoltaic Technology

4.3.1 Evolutionary Patterns of Photovoltaic Technology

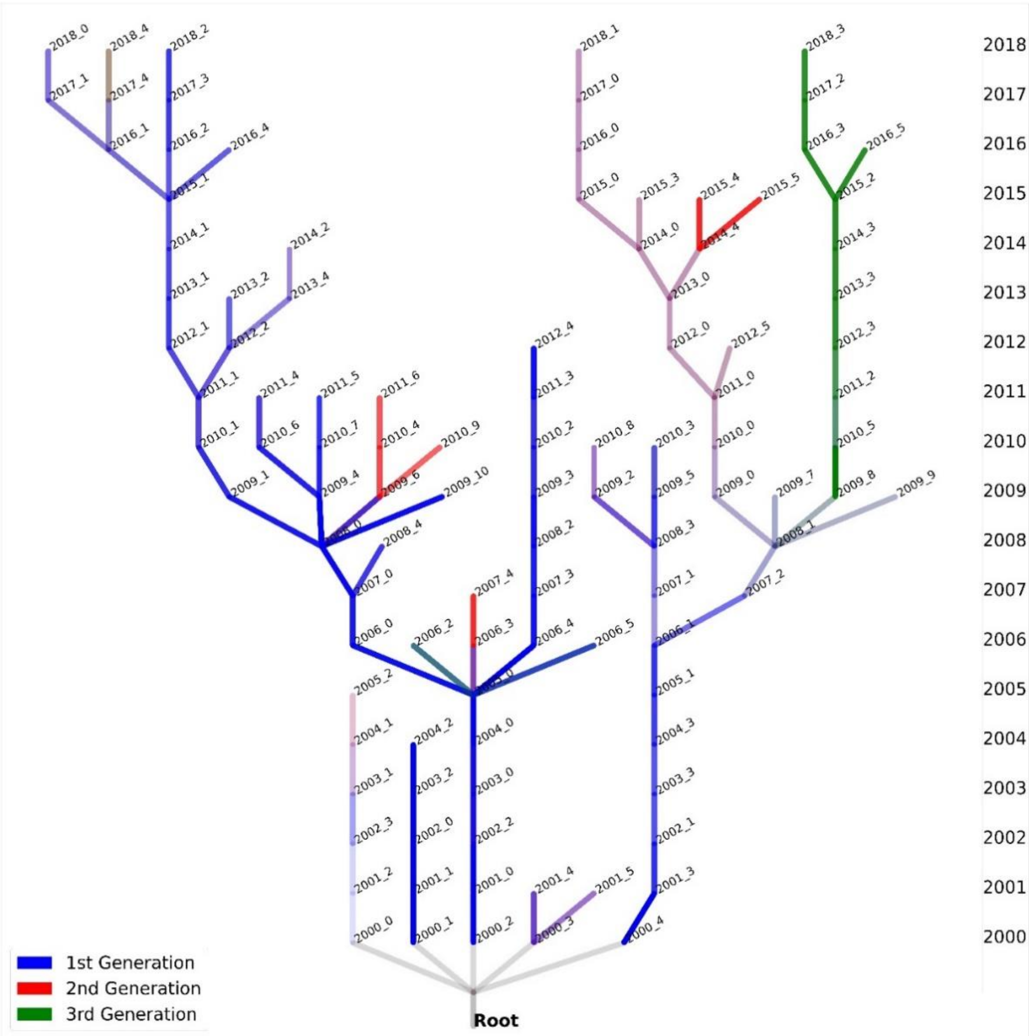


Figure 4-2. Photovoltaic technology phylogenetic tree

The evolutionary phylogenetic tree of photovoltaic technology is presented in **Figure 4-2**. The y-axis represents the period from 2000 to 2018 and the root point on the x-axis indicates the starting point. Technology taxa have existed since 2000, and the name of the taxon has been specified as [YYYY-ID]. The longitudinal solid line connecting the technology taxon is called a branch, which expresses the ancestor-descendant relationship between taxa. Each branch is marked in different colors depending on the technology classification in **Table 3-1**: blue, red, and yellow for the first, second, and third generations, respectively. The color depth is the weight of the IPC code according to technology classification. In the case of branches from [2017_0] to [2018_1] for example, the color appears purple, which indicates a similar IPC code share of first- and second-generation technologies in one lineage. The IPC codes of general-purpose technologies are not reflected in the color representation of the phylogeny as they cannot be specific to a technology generation. The basic information and terminology needed to interpret the phylogenetic tree are shown in **Figure 4-3** (Gregory, 2008).

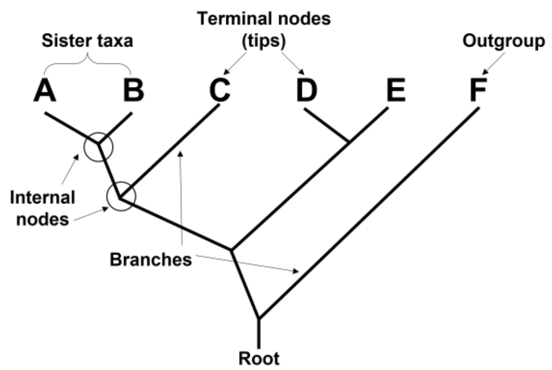


Figure 4-3. Anatomy of phylogeny
(Author reproduction based on Gregory (2008))

4.3.1.1 Evolutionary Patterns of Photovoltaic Technology

Through this phylogenetic tree, the overall evolution of photovoltaic technology can be observed. As shown in **Figure 4-4**, photovoltaic technology was divided into five taxa. At the start point, the year 2000, photovoltaic technology consisted mainly of first-generation technologies. Of these, four taxa, except for [2000_3], were retained until 2004 and 2005. The [2000_2] taxon shows a red branch with an increasing proportion of second-generation technologies from 2003, but the rest of the taxa continued the pattern of technology evolution centered on the first-generation technology.

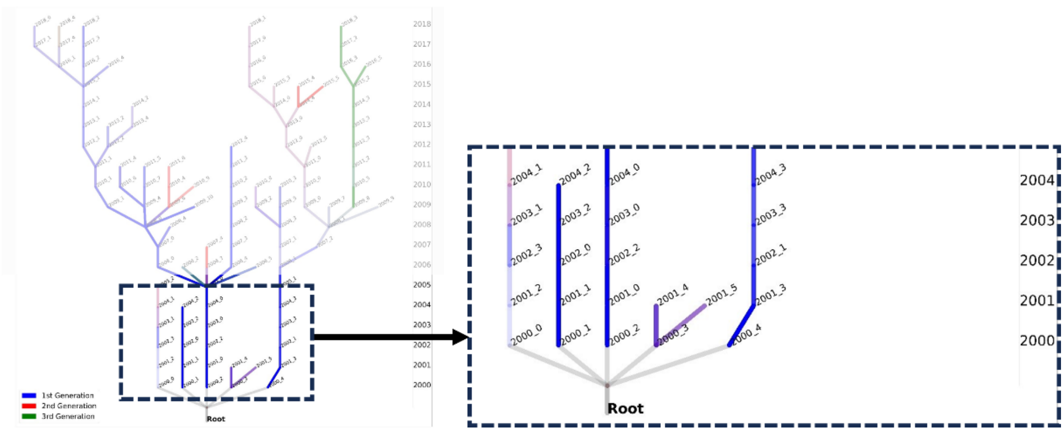


Figure 4-4. Evolutionary patterns in period 1: retention

This evolutionary pattern changed significantly between 2005 and 2006 (See **Figure 4-5**). [2000_2] and [2000_4] speciated after 2005 and 2006, respectively, leaving many lineages and descendants, but the rest went extinct. Thereafter, active speciation is observed. For the first, the taxon [2005_0] speciates into five taxa in 2006. Among the differentiated descendant taxa, however, only [2006_0] and [2006_4] are passed on, and the descendant of [2006_1] becomes the terminal node of the first generation of technology. On the other hand, the descendants of [2000_4] exhibit both cladogenesis and anagenesis[32]. The descendants of [2000_4] passed down until 2006 diverged from [2006_1] as nodes into [2007_1] and [2007_2], and the technological characteristics of the lineage represented by color began to change. The descendants of [2007_2] continued to evolve, varying their technological characteristics on an ongoing basis, giving rise in 2018 to the final descendants of a mix of first- and second-generation and third-generation technologies.

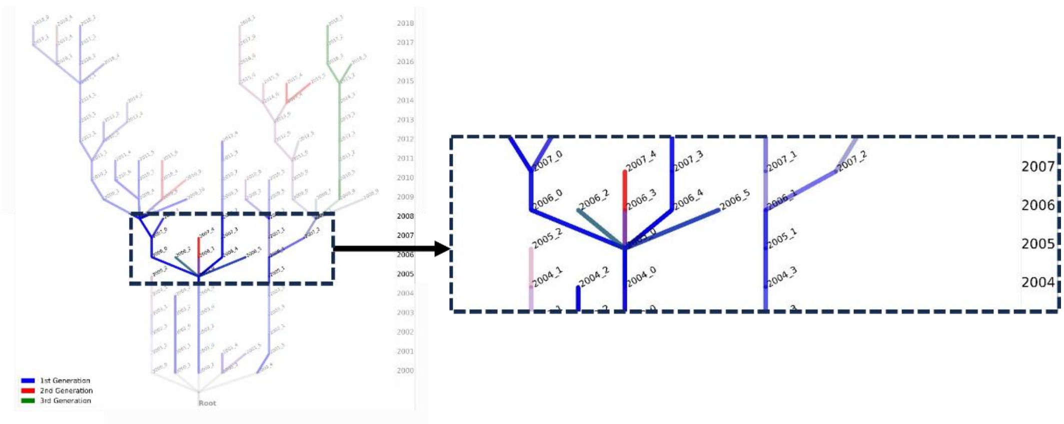


Figure 4-5. Evolutionary patterns in period 2: speciation

Speciation was most frequently observed from 2008 to 2010, as in **Figure 4-6**. The five taxa in 2008 gave rise to eleven descendants in 2009, followed by ten and seven in 2010

[32] Anagenesis is defined as the continued existence of an interbreeding population through the gradual evolution of a species, while cladogenesis means that a branching or splitting occurs, leading to two or more lineages, creating separate species (Futuyma, 2009).

and in 2011, respectively.

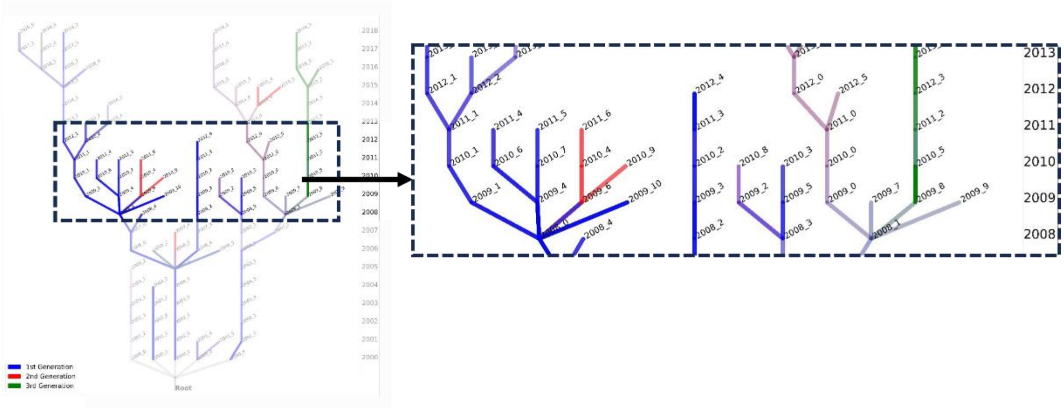


Figure 4-6. Evolutionary patterns in period 3: aggressive speciation

All taxa present in 2018, the end of the analysis period, are descended from [2000_2] and [2000_4]. A clade in which [2018_0], [2018_2], and [2018_4] have [2000_2] and [2008_0] as common ancestors. The three taxa [2018_0], [2018_2], and [2018_4] co-evolved along the lineage originating from [2000_2] and diverged from the [2015_1] taxon. All of these taxa are composed of first-generation and modular technologies, but anagenesis (color change) is observed in the other two taxa except for [2018_2]. In particular, [2018_4] is more strongly characterized by second- and third-generation traits, making it stand out from its sister taxa. This implies that a new evolutionary pattern has emerged in this technical taxon since 2018, or that extinction is likely.

[2018_1] and [2018_3] are another clade, with [2000_4] and [2008_1] as common ancestors. [2018_1] and [2018_3], descendants of [2000_4], exhibit very different evolutionary trajectories in their technological characteristics after separating from the [2008_1] taxon. While [2018_1] is a mixture of first- and second-generation technology, [2018_3] is composed of third-generation technology. Second and third generation technologies share the commonality of being less mature than first generation technologies. Second-generation technologies temporarily formed an independent lineage (red) through [2006_3], [2009_6], and [2014_4], but soon became extinct and were passed down along the lineage of [2018_1], coexisting with first-generation technologies. Meanwhile, the third-generation technology established a very distinct lineage through the taxa [2008_1] and [2009_8].

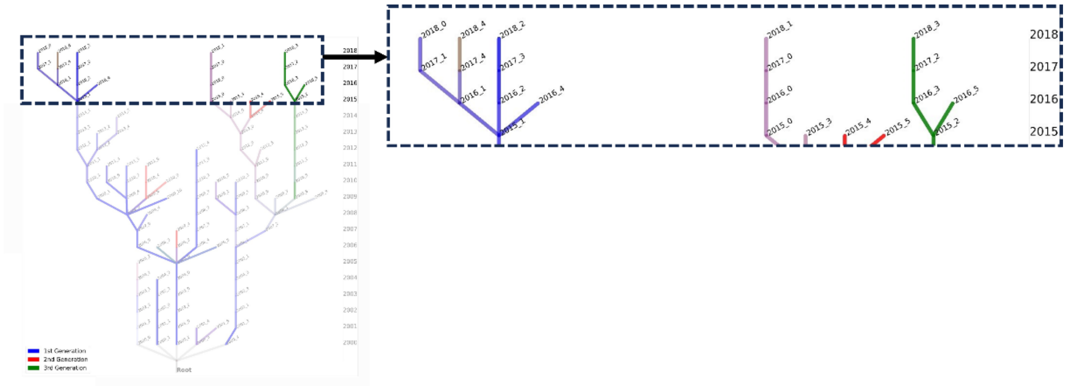


Figure 4-7. Evolutionary patterns in period 4: mostly retention

Table 4-3 provides a brief description of the photovoltaic technology evolution resulting from this work.

Table 4-3. Summary of evolutionary patterns observed in photovoltaic technology

Time period	Brief description of technology evolution
Period 1 (2000-2004)	Retention period of most taxa, mainly composed of the 1st generation technology
Period 2 (2004-2008)	Speciation of [2000_2] and [2000_4] taxa and extinction of others
Period 3 (2008-2013)	Aggressive lineage speciation Both cladogenesis and anagenesis after [2008_1]
Period 4 (2013-2018)	Mostly retention along to lineage Anagenesis after [2015_1]
The entire Period (2000-2018)	Gradual evolution along the technology lineage formed by genetic similarity Two common ancestors in 2000, mainly composed of the 1st generation technologies Five descendants in 2018, divided into three groups: 1st generation technology group, 1st and 2nd generation mixed group, and 3rd generation technology group, respectively

4.3.1.2 Validation of Technological Phylogenetic Tree: Qualitative Comparison with Historical Facts

The validity of a technology evolutionary phylogenetic tree is based on how well it can identify and describe the actual history of a technology. The following discussion compares the photovoltaic evolutionary phylogenetic tree derived in this study with the developmental history of photovoltaic technology. The following discussion refers to the photovoltaic technology and industry review presented in Chapter 3 and Table 3-2.

Table 4-4 provides overall summary based on the previous tables including the events that occurred during each period (Table 3-2), evolutionary patterns on the phylogenetic tree (Table 4-3), and major taxa and keywords. The keywords of the taxon are derived by using the TF-IDF method in the process of constructing the evolutionary phylogenetic tree. The top five keywords representing the taxon are drawn, as well as keywords that were not present in the direct ancestors but newly appear in the taxon. It should be noted that a new keyword does not mean the first appearance of the patent containing the content.

Suarez et al. (2015) apply the notions of socially negotiated "category emergence" (e.g., Bowker & Star, 2000) to strengthen their time-to-market theory. They propose a "dominant category," defined as the category in which a company chooses to position its products, the conceptual schema adhered to by most stakeholders in a product category and argue that a window of opportunity opens between the maximum point of the dominant category and the dominant design.

The major and new keywords for taxa presented in Table 4-4 correspond to the definition of product categories by Suarez et al. (2015) as technological categories. Changes in the categorical positioning of major taxa over the course of technological evolution are utilized to complement the qualitative interpretation.

Table 4-4. Qualitative comparison for validating evolutionary phylogenetic tree

Time period	Historical facts	Evolutionary pattern	Major taxon	Top 5 keywords of taxon (Newly emerging keywords)
Period 1 (2000-2004)	Industrialization Dominant design (Al-BSF)	Retention	[2000_0]	*vapor, hetero, metallic, diffusion, compound*
			[2000_1]	*tile, solder, moistureproof, sheet, degradation*
			[2000_2]	*roof, plate, epoxy, hole, encapsulation, cost*
			[2000_4]	*color, diffraction, plastic, appearance, reflection*
Period 2 (2004-2008)	Polysilicon shortage (2004)	Extinction Speciation	[2005_0]	*plate, separation, groove, resin, mirror (antimony, sb, oxidizing, heterojunction)*
			[2006_1]	*lead, pattern, thickness, diffusion, silicone (polyorganosiloxane, hydrosilylation, olefin, diorganopolysiloxane)*
Period 3 (2008-2013)	Global crisis (2008)	Speciation (Cladogenesis & Anagenesis)	[2008_0]	*control, reflector, input, bandgap, radiation (truss, signal, scribe, depression, epistructure)*
			[2008_1]	*paste, diffusion, electron, quantum, finger (nanotube, fullerene, zn, silicide, polythiophene)*

Period 4 (2013-2018)	New dominant design (PERC)	Retention (Anagenesis)	[2013_0]	*paste, emetter, subcell, impurity, silver (cmt, indentation, bristle, mc, braid, perovskite)*
			[2015_1]	*module, sheet, panel, tile, frame (ldpe, lldpe, pontoon, hexamethylene)*
Major terminal nodes			[2018_1]	*paste, selenium, aluminum, copper, powder (disparity, etcs, sicy, dh, mgxcd, cyanide)*
			[2018_2]	*housing, wall, panel, mirror, dust (configurability, instruct, chiller, screening, blackbody)*
			[2018_3]	*carbon, nanotube, polymer, perovskite, triplet (micelle, benzotrichalcogenophene, subunit)*

By dividing the analyzed period into four periods, the evolution of photovoltaic technology can be categorized into retention (period 1, period 4) and speciation (period 2, period 3). Interestingly, the retention period is the time of emerging dominant designs, while the speciation period is characterized by external environmental shocks.

First, the retention pattern is observed in periods 1 and 4. Period 1 was the beginning of the photovoltaic industrialization, where the main issue was to reliably mass-produce the standard technology of first-generation silicon photovoltaic cells (Green, 2005; Kazmerski, 2006; Wand & Leuthold, 2011; Wilson et al., 2020). The so-called conventional solar cell, a structure with an aluminum back surface field (Al-BSF) on a p-type silicon wafer, was chosen as the dominant design for the industry.

One of the key implications of the emergence of a dominant design is that it shifts the relative focus of R&D efforts from product innovation to process innovation (Abernathy & Utterback, 1978). This fundamental change in the nature of innovation is represented in the evolutionary phylogenetic tree by the retention of lineages, which is observed in the years of the early 2000s. The representative keywords of the common ancestor [2000_2] and [2000_4] in the evolutionary tree capture such concerns of the early photovoltaic industry. The [2000_2] taxon represents technologies close to the early dominant designs with keywords for facing market and economic challenges such as *roof* and *cost*, and process technologies for performance, durability, and reliability of crystalline silicon photovoltaic cells (*plate, crystal, diode, junction*) and modules (*epoxy, encapsulation*). On the other hand, [2004_4] is characterized by the inclusion of keywords with relatively high technological flexibility compared to [2000_2], such as *color, diffraction*, and *plastic*. In addition, the taxa [2000_0] and [2000_1], representing process and modular technologies, respectively, were inherited and carried forward 2004 and 2005.

While the dominant design in Period 1 was related to the industrialization process, the dominant design that emerged in Period 4 resulted from technological discontinuities caused by environmental uncertainty (Anderson & Tushman, 1990). After an era of ferment, first-generation technologies that continued to innovate processes and products settled on PERC, one of high efficiency cell structures, as new dominant design to replace Al-BSF cells (Baliozian et al., 2020; Chawla et al., 2020; Wilson et al., 2020).

Meanwhile, wafer size and thickness changes require material and process improvements for surface passivation layers. This has created an opportunity for second-generation thin-film technology, based on deposition technology, to converge with first-generation technology. Furthermore, to compensate for the physical limitations of materials and to secure light absorption across the entire wavelength range, tandemed photovoltaic cells have been actively developed (Green et al., 2014; Tonui et al., 2018), and TOPCon (Tunnel Oxide Passivated Contact) photovoltaic cells have been triggered to develop bifacial modules and building integrated photovoltaic modules. The issue of lifecycle and recycling of photovoltaic modules under the theme of sustainability accelerated the overall development of module technology (Frischknecht et al., 2015; Wang et al., 2022; Wilson et al., 2020).

The factual history of period 4 described so far is observed in the phylogenetic tree as an anagenesis pattern. Specifically, even though they exhibit the pattern of retention as same, in Period 1, the technological characteristics of the ancestors were passed down with the same, while in Period 4, they changed in color. Lineages with a mix of first- and second-generation technologies, such as the [2013_0] taxon, further expanded the range of technologies by adding keywords for materials and structures, such as *CMT (Cadmium-Manganese-Telluride), indentation,* and *bristle,* based on basic photovoltaic cell technology keywords such as *paste, emitter*, and *impurity*. Meanwhile, the lineages with [2000_2] and [2008_0] as common ancestors evolved with a distinct blue coloration, but in the [2015_1] taxon, new keywords were added from materials such as *ldpe, lldpe*, and *hexamethylene* to *pontoon*, which refers to a buoyancy system, to differentiate the technological characteristics of subsequent descendants.

Second, a pattern of speciation is observed in Periods 2 and 3. Especially around 2005 and 2008, technological speciation is active. The shock that triggered the 2005 speciation was the polysilicon supply crisis from 2004. This event acted as a selection mechanism for technological evolution, leading to the extinction of some taxa, but also revitalized technological development in various fields as a warning of raw material instability. The first-generation crystalline silicon photovoltaic cells were an axis of photovoltaic technology during this period, and efforts were made to mass-produce high-efficiency photovoltaic cells to break away from material dependence on polysilicon and secure price competitiveness due to its high cost (Green, 2019b).

The other axis was investment in second-generation thin-film and third-generation emerging photovoltaic cell technologies, which the industry sought to use as alternatives to crystalline silicon photovoltaic cells. This spurred the mass production of second-generation technologies, leading to an increase in the market share of thin-film PV from 5.5% in 2004 to 11.4% in 2007 and 13.4% in 2010 (Gan & Li, 2015; Kirkegaard et al., 2010; Price et al., 2010).

The internal node [2005_0] leads to five descendant taxa, each characterized by a first-, second-, and third-generation technology in 2006. This cladogenesis resulted from new keywords introduced into [2005_0]. While the keywords represented in [2005_0] consist of technologies to increase the efficiency of first-generation cells on thinner substrates, such as *plate, separation*, and *groove*, the new keywords consist of thin-film and next-generation technologies, such as *antimony, sb, oxidizing*, and *heterojunction*.

The descendant of [2000_4], [2006_1], a taxon from a different family around the same time, also shows a broadening of the technological category due to the influx of keywords such as *polyorganosiloxane, hydrosilylation*, and *olefin*.

The global crisis that broke out in 2008 triggered cladogenesis. The photovoltaic industry, which has a high proportion of government-generated demand, was directly affected. Moreover, the increase in the number of entrants and the aggressive capacity expansion of Chinese companies caused an oversupply situation. Competition in the industry intensified, module prices dropped dramatically, and a shake-out occurred in which uncompetitive companies exited.

During this industrial reorganization, photovoltaic technology has continued its efforts to differentiate itself for survival, and this is expressed as the speciation phenomenon in the technology evolutionary tree. In [2008_0], keywords such as *control, reflector, input*, and *bandgap* were joined by system elements such as *truss* and *signal*, process technologies such as *scribe* and *depression*, and material technologies such as *epistructure*, giving birth to four descendant taxa in 2009. In this taxon, technologies that are highly related to the first-generation technologies led to the [2018_2] taxon with keywords such as *housing*, *dust*, and *blackbody*.

In fact, companies mass-producing first-generation technologies have attempted to secure technological competitiveness by producing high-efficiency photovoltaic cells that have only been realized in the laboratory, such as PERC, IBC, and SHJ instead of Al-BSF photovoltaic cells, which have become more common under the intense competitive environment (Khatibi et al., 2019; Wilson et al., 2020). To this end, the existing p-type silicon substrate was diversified to an n-type base, and elemental technologies such as selective emitter formation technology, rear side localized junction structure technology, and electrode formation technology through plating or laser transfer were developed (Chawla et al., 2020; Green, 2019a, 2019b).

On the other hand, unlike Period 2, where most of the speciated branches became extinct within a short period of one or two years, Period 3 showed a cladogenesis as the branches went through their own evolutionary process and later became the terminal nodes of [2018_1] and [2018_3]. Their internal node, [2008_1], coexists with keywords representing first- and second-generation technologies such as *paste, diffusion, electron,* *finger, zn,* and *silicide*, and third-generation technologies such as *quantum, fullerene,* and *polythiophene*. Since then, it has evolved into a mixed system of first- and second-generation technologies represented by keywords such as *paste, selenium, aluminum,* and *copper* ([2018_1]), and third-generation technologies such as *carbon, nanotube, polymer,* and *perovskite* ([2018_3]).

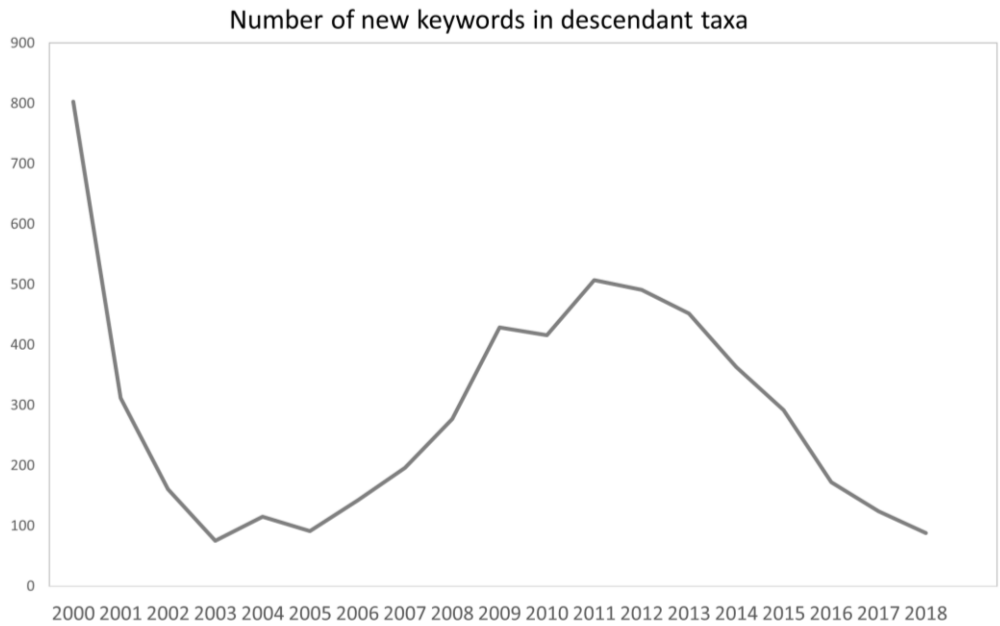


Figure 4-8. Number of new keywords in descendant taxa

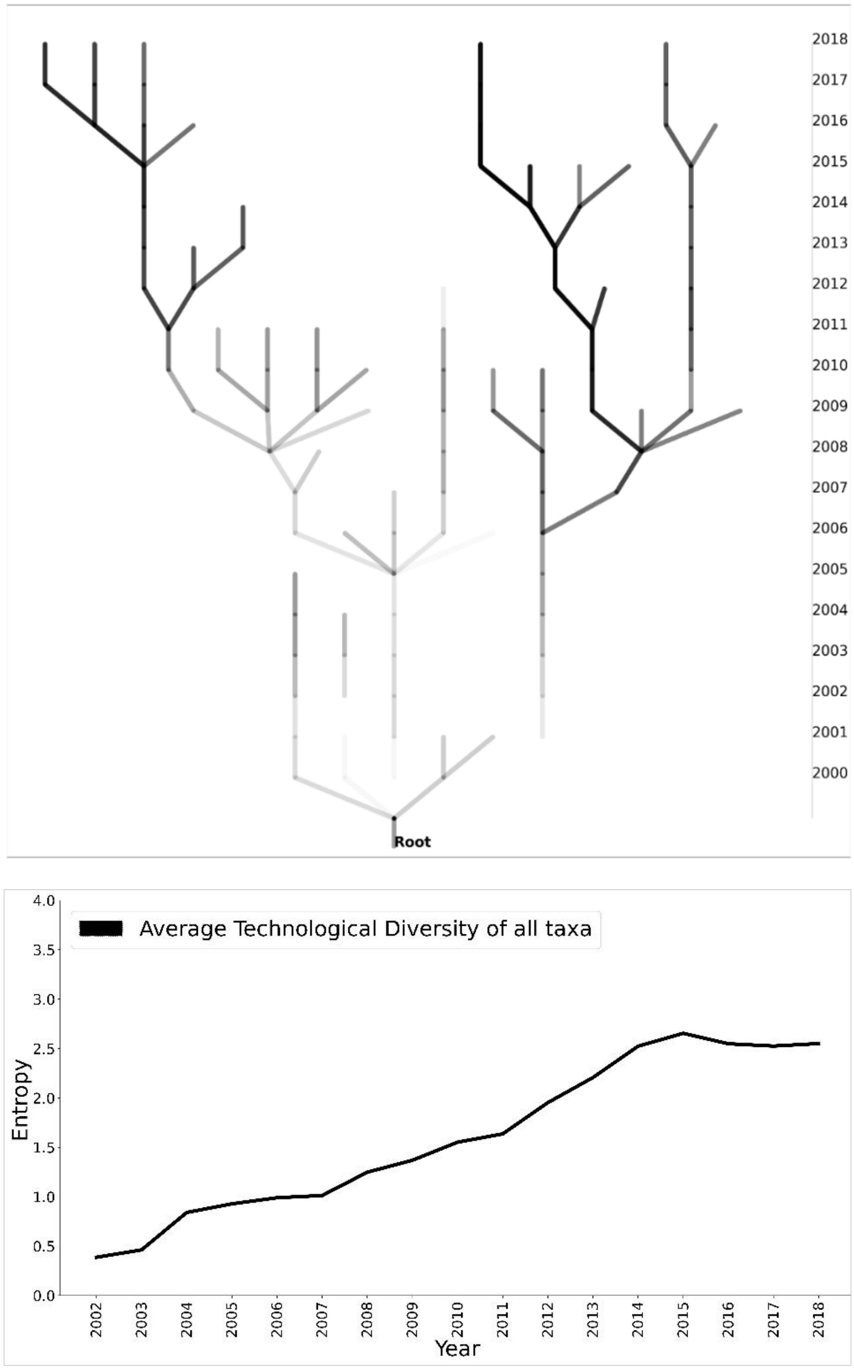
Figure 4-8 describes the number of new keywords by year. The number of new keywords decreased in the retention pattern (periods 1 and 4) while increased in the speciation pattern (periods 2 and 3). Anderson and Tushman (1990) presented an evolutionary model of technological change, empirically tested by the cement, glass, and small computer industries. In an era of incremental change, the matured dominant design passes into an era of ferment, where technological competition accelerates and technological discontinuities occur, leading to the emergence of a new dominant design, which in turn results in a period of incremental improvement. The results in Figure 4-4 illustrate the technology cycle through the simple metric of new keyword appearances, and suggest that this process is also related to evolutionary patterns.

In this section, the results confirm that the phenomena observed in the phylogenetic tree correspond with the actual history of photovoltaics. In summary, photovoltaic technology has interacted with the given environment, and the micro-variations accumulated in the process evolved gradually, fostering descendants like their ancestors but with relative superiority.

4.3.2 Diversity Dynamics by Trajectory in Photovoltaics

Figure 4-9 represents the diversity dynamics on photovoltaic technology evolution. First, **Figure 4-9 (a)** shows the level of entropy, that is the technological diversity, on taxa in the evolutionary phylogenetic tree constructed in Section 4.1. The darkness of the color indicates the level of diversity, with black being darker closer to 2018 than to the early 2000s. Next, **Figure 4-9 (b)** is the average change in diversity for all taxa, and both results in Figure 4-3 imply that photovoltaic technologies have evolved in the direction of increasing diversity. In fact, the number of sub-group IPC codes in taxa has increased from 16 in 2000 to 179 in 2018. However, as shown in (b), the diversity of photovoltaic technologies has stagnated until recently, with a slight decline starting in 2015.

As shown in the previous section, taxa in 2018 have [2000_2] and [2000_4] taxa as common ancestors. Taxon [2000_2] evolved around first-generation technology, while taxon [2000_4] evolved with second- and third-generation technology, including first-generation. In (a) of Figure 4-9, descendants of the [2000_2] taxon, which has mostly first-generation technology, are less diverse than descendants of the [2000_4] taxon. For the [2000_4] lineage, the diversity level increases significantly after 2006, whereas for the [2000_2] lineage, a differential change in diversity level is observed after 2009. These results are consistent with discussions in the previous section in the context of the silicon supply crisis at *period 2* and the competitive environment at *period 3*.



(a)

(b)

Figure 4-9. The level of diversity of photovoltaic technology
(a) Diversity dynamics on phylogenetic tree, (b) Average Diversity of all taxa

Figure 4-10 represents the diversity dynamics for the major technological trajectories that evolve from root to [2018_1], [2018_2], and [2018_3]. Each trajectory represents the first-generation ([2018_2], blue), the mixture of first- and second-generation ([2018_1], purple), and third-generation ([2018_3], green) technologies existing in 2018. Technology diversity is measured along the major trajectories of the phylogenetic tree, and then the three simple moving average (3-SMA) method is applied to express a smooth trend.

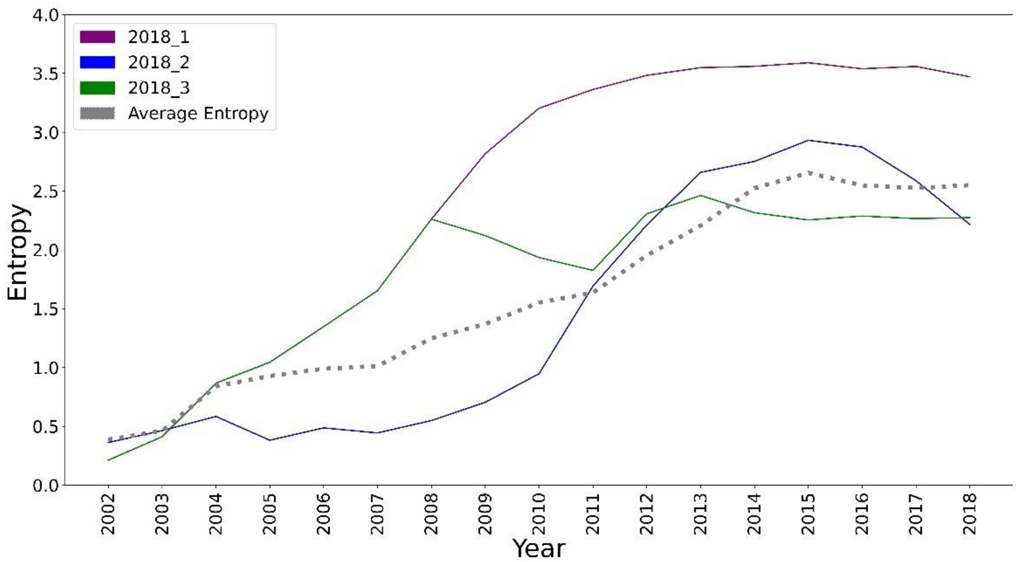


Figure 4-10. Diversity dynamics for major technological trajectories

The diversity dynamics of each trajectory is different from the average diversity dynamics shown in Figure 4-9 (b). While the diversity of overall photovoltaic technologies showed a gradual increase before 2015, each of diversity in major trajectories has a distinctly different trend.

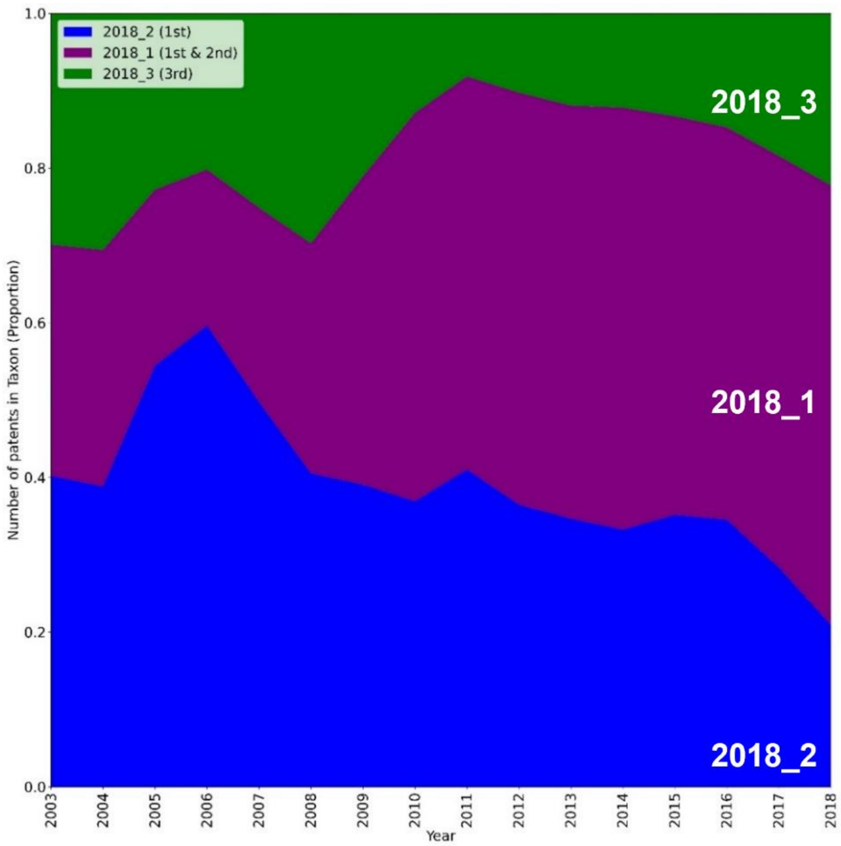
First, in the [2018_2] trajectory results, which represent the evolution of first-generation technologies, diversity was lower than the average of all technologies before 2011 and showed a stagnant trend without a significant increase. This reflects the reality that first-generation technologies in the early years of industrialization pursued incremental innovations based on the already established dominant design of Al-BSF cells. The diversity of first-generation technologies grows rapidly after 2011 before declining after 2015.

Second result is the trajectory from Root to the [2018_1] Taxon, which consists of a mix of first and second-generation technologies. In the case of the trajectory, with the exception of the early 2000s, the diversity was higher than the average for photovoltaic technology. It means constantly exploring new combinations of technologies to keep the technology evolving.

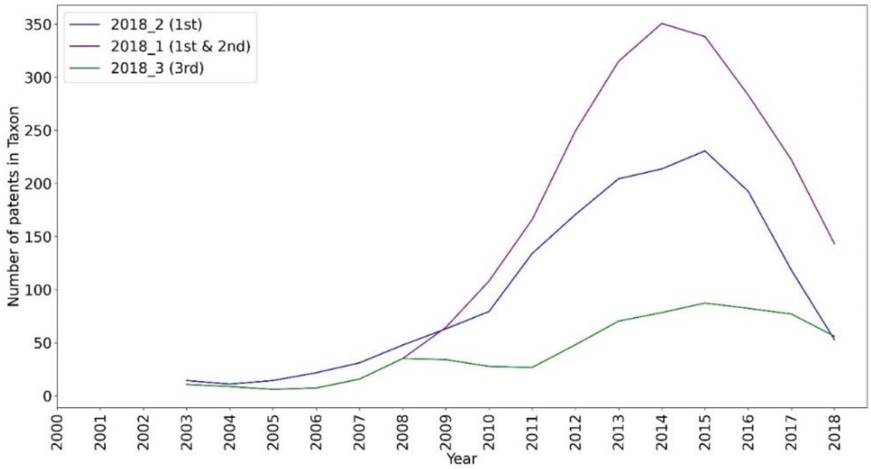
Last is the trajectory of [2018_3] composed of third-generation technologies. This trajectory was the same as that of [2018_1], but after speciation in 2008, technological diversity showed decreasing and stagnating patterns. This is in line with the fact that during the photovoltaic industry recession, third-generation technology development was relatively slow due to lack of funding. Third-generation technologies remain below the average of photovoltaic technology diversity. Therefore, the task of the current third-generation technologies is to improve technology diversity through the introduction and combination of new technologies.

The evolutionary approach is a historical science grounded in the past (Nosil et al., 2020). It is nearly impossible to accurately predict the future direction of evolution because the causes and effects of evolution change over time under complex and uncertain conditions. However, patterns of evolution from the past can provide macro direction. This is especially true for the path-dependent and cumulative nature of technology evolution.

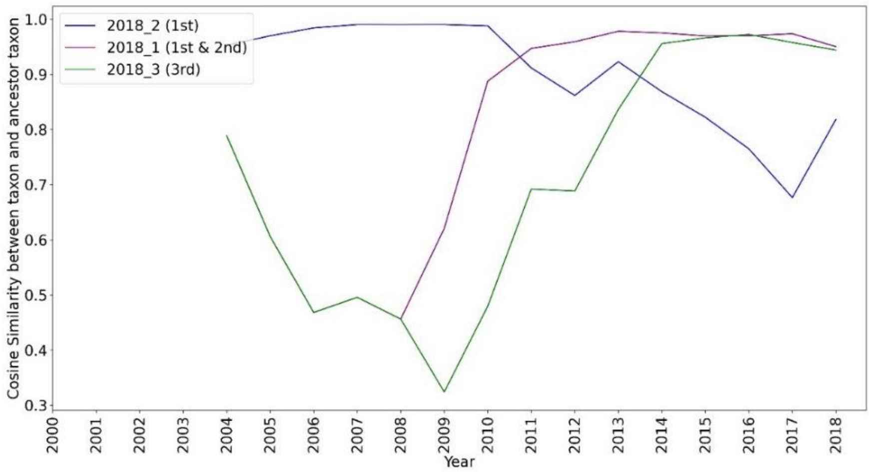
Figure 4-11 is a diagram of the information derived from the technology evolutionary tree. By integrating the technological diversity dynamics on the major taxa presented above, it is possible to forecast the basic direction of future photovoltaic technology evolution.



(a)



(b)



(c)

Figure 4-11. Information from evolutionary phylogenetic tree
(a) Proportion of patents per trajectory
(b) Number of patents per taxon in each trajectory
(c) Cosine Similarity between ancestor and descendant taxa

For the three main trajectories, (a) is the ratio of patents per trajectory to the number of patents in a certain year, (b) is the change in the number of patents per taxon in each trajectory, and (c) is the change in the cosine similarity of ancestral and descendant taxa within the lineage. (a) and (b) can be considered as indicators of the quantitative aspect of evolution (whether there are enough descendants) while (c) as the qualitative aspect (whether genetic relationships are robust).

(a) and (b) can be viewed as indicators of the quantitative aspects of evolution (whether there are enough descendants) and (c) can be viewed as indicators of the qualitative aspects (whether genetic relationships are strong). First, through (a) and (b), we observe that the number of patents per taxon is decreasing in all three trajectories, and that especially patents for first-generation technology are becoming a smaller share of total patents. A decrease in descendant individuals is evolutionarily unfavorable because it leads to a reduction in genetic diversity and a weakening of adaptive potential (Lande, 1988; Makert et al., 2010). Specifically, population decline means that only a fraction of the genetic diversity present in an individual survives to contribute to the next generation, which is equivalent to losing the unique genetic information present in the population. This reduces the likelihood of adaptive traits or variations that help the population survive and reproduce under different conditions, leading to a reduction in evolutionary adaptability and resilience. A smaller population is more vulnerable to stochastic events occurring in the external environment, and ultimately, a decrease in the number of descendants increases the risk of extinction of the population.

In (c), the degree of evolutionary relationship between the descendant taxon and the ancestor is different for each lineage. While [2018_2] shows a high cosine similarity and has been declining since 2010, [2018_1] and [2018_3] have been increasing after an initial decrease and are now maintaining a strong evolutionary relationship. The higher the value of cosine similarity, the stronger the evolutionary relationship. The similarity between ancestors and descendants and the large number of shared traits and characteristics indicates that the common ancestor is recent.

In phylogeny, the degree of relationship between ancestors and descendants is related to the dynamic process of evolution (Freeman & Herron, 2007; Lemey et al., 2009). During evolution, individuals accumulate genetic differences over time as they adapt to various environmental and ecological niches; therefore, changes in the similarity of evolutionary relationships indicate that descendants have undergone significant evolutionary change, either by acquiring new traits or by losing or modifying existing traits (Freeman & Herron, 2007). Weak ancestor-descendant relationships occur when new lineages emerge and diversify, or when genetic traits are reduced due to genetic drift, selection mechanisms, or other causes, leading to the formation of new species or, conversely, extinction. Strong evolutionary relationships emerge when populations undergo stable selection, genetic convergence, or experience environmental stability, resulting in high levels of evolutionary conservation. Ancestral traits have an evolutionary adaptive advantage, contributing to their continued retention.

To summarize Figures 4-10 and 4-11, the following points can be made. First, the first-generation technology taxon [2018_2] are experiencing a decline in technology diversity and the number of patents in the lineage, and their evolutionary relationships are weakening. In particular, the proportion of total patents is decreasing, which is interpreted as an endangered species. Second, the mixed technology taxon [2018_1], which is a combination of the first and second generations, shows stagnant technology diversity and a decrease in the number of patents, but an increase in the proportion of total patents. It also maintains a high evolutionary relationship. Especially, it has the highest number of patents and a high diversity value among three major trajectories, which is expected to be passed on to subsequent generations. Finally, the third-generation technology of [2018_3], like [2018_1], shows stagnant diversity and a decrease in the number of patents, but a noticeable increase in quantitative weight and a strong ancestor-descendant relationship. However, while [2018_3] shows an increasing proportion within the total number of photovoltaic patents, the small number of patents in absolute terms may pose an evolutionary threat. While they are expected to persist in the absence of significant external environmental change, there is a need to improve evolutionary adaptability and flexibility through population growth.

This section examines how diversity has changed over the evolution of photovoltaic technology. After reviewing the diversity dynamics of photovoltaic technology in an overall context, the detailed dynamics of key trajectories are discussed. Overall, photovoltaic technology has seen a gradual increase in diversity, but it appears to have stagnated after a slight decline since 2015. The major trajectories for photovoltaic are identified as a first-generation technology trajectory ([2018_2]), a mixed first- and second-generation technology trajectory ([2018_1]), and a third-generation technology trajectory ([2018_3]). Each trajectory has repeatedly varied in diversity over the course of technology evolution, with differentiated diversity dynamics across technologies. However, in all three trajectories, stagnant or declining diversity levels in current technologies are also observed.

These results point to a weakening of the current innovation momentum in photovoltaic technology. Moreover, based on the diversity dynamics of each major trajectory and the quantitative and qualitative evolutionary indicators derived from the evolutionary phylogenetic tree, the subsequent technological evolution is predicted to be extinction for the first-generation technology trajectory, and retention for the technology mixing trajectory and the third-generation technology trajectory.

This study proposes that technological diversity dynamics should be quantified by considering technological trajectories. The analysis in this section shows that there are differences in the diversity dynamics at the aggregate technology level and at the detailed trajectories. Furthermore, diversity varies across trajectories in different ways depending on technological characteristics. These findings suggest that it is reasonable to investigate the dynamics of technological diversity by considering detailed trajectories. By examining the dynamics of technological diversity over trajectories, it is feasible to explore the technological evolution in detail and identify trajectories with high innovation potential.

4.4 Sub-conclusion

Technological diversity is the seed of development. Existing studies have already comprehensively analyzed technological diversity at the agglomeration level (Anderson & Tushman, 1990; Gao et al., 2013; Lin et al., 2021). However, despite much discussion on technological diversity, to the best of our knowledge, no study has considered the space where technologies vary and grow.

Technology forms a trajectory over time (Dosi, 1982). More precisely, technologies at the sublevel form detailed trajectories over time. They are then divided into new trajectories that differentiate them from existing technologies or, alternatively, disappear (Tellis and Crawford, 1981). Technology development is the process by which one or more of these trajectories come together to form a space. Therefore, in order to develop a more concrete technology strategy, it is necessary to identify the detailed trajectories that are currently being formed in the industry and to measure the technological diversity of each trajectory.

To fill this gap and make specific suggestions for innovation, this study uses a phylogenetic tree methodology from an evolutionary perspective to examine the dynamics of technological diversity by considering the spatial information of technological change (J.-D. Lee et al., 2022).

For the empirical analysis, this study uses 8,081 patents granted by the USPTO for photovoltaic technology from 2000 to 2018 and the IPC code information of each patent. The results are summarized as follows:

First, the evolutionary phylogenetic tree of photovoltaic technology fully describes the technological and industrial history of photovoltaics. This result provides robustness for considering the dynamics of technological diversity in the evolutionary phylogenetic tree. Photovoltaic technologies have gradually evolved by interacting with the external environment. It has evolved into five taxa classified into three technological categories: first-generation ([2018_0], [2018_2], [2018_4]), first- and second-generation mixtures ([2018_1]), and third-generation technologies ([2018_3]).

Second, the dynamics of technological diversity in the aggregate level of technologies are different from those in the trajectory-specific technologies. The overall diversity of photovoltaic technologies has gradually increased over the evolutionary process. However, drastic changes have been observed in the major technological trajectories, and there are differences in the diversity dynamics of each trajectory depending on the technology characteristics.

Third, in the subsequent evolution of photovoltaic technologies, first-generation technologies are predicted to become extinct, while mixed first- and second-generation technologies and third-generation technologies are predicted to be transmitted. These findings are based on quantitative and qualitative evolutionary metrics derived from diversity dynamics and evolutionary phylogenetic tree along key trajectories. However, for third-generation technologies, the low number of individuals (number of patents) increases the risk of evolutionary adaptation, which needs to be complemented to ensure sustainable development.

Diversity is a necessary condition for evolutionary mechanisms (Basalla, 1988). Technological diversity is associated with an industry's competitiveness, innovation potential and adaptability to market changes. High technological diversity promotes innovation and competition and stimulates markets, while low technological diversity reduces the dynamism of competition and makes an industry potentially vulnerable to disruptive innovation from other industries (Argot & Ingram, 2000; Frenken et al., 2000; Hanusch, 2000).

The diversity of photovoltaic technology has fluctuated throughout the evolutionary process. However, the current situation is stagnant in diversity dynamics. As of 2015, the diversity trend has stagnated or even decreased, decreasing in the first generation, stagnating at a high diversity level in the first and second-generation mixtures, and stagnating at a low diversity level in third-generation technologies.

Decreasing diversity indicates a weakening of the driving force in photovoltaic technology development. Based on industry lifecycle theory, a sustained reduction in technological diversity in a photovoltaic industry that is currently passing through its maturity phase will eventually lead to decline (Markard, 2020). The practical implications for photovoltaic technology are comprehensively discussed further in Chapter 7.

Chapter 5. Technological Search to the Diversity Dynamics of Technology

5.1 Patterns of Technological Search on Evolutionary Approaches

Diversity in technology increases through the recombination of technological elements (Frenken, 2006; Wagner and Rosen, 2014) and changes depending on the purpose and path of search the technology (Carignani et al., 2019; Gao et al., 2013; Lin et al., 2021; Song et al., 2019). As reviewed in Chapter 2, previous literatures on technology search have explained the patterns of search based on the concept of distance (e.g., Stuart & Podolny, 1996) or scope and depth (e.g., Katila & Ahuja, 2002). However, a technology search takes place within the space where technology trajectories are forming; therefore, it is necessary to consider not only the distance but also the direction of the search. To Clarify the endogenous mechanisms of how diversity increases, decreases, or stagnates, it is necessary to further refine the search patterns of technologies.

The evolutionary approach allows us to examine technology searches in more detail. In other words, it is possible to grasp not only the integrated consideration of distance and direction but also the origin of newly introduced technologies. In biology, there are three methods used to ensure genetic diversity (Carignani et al., 2019; Kardong, 2008; Lawrence, 1999).

Vertical Inheritance (VI) is a method in which descendants receive number of genetic information from direct ancestors (Lawrence, 2005). There are ancestors that are standard for evolution, and they convey the basic framework of genetic makeup (Carignani et al., 2019; Wagner & Rosen, 2014). Descendants pursue gradual evolution based on the inherited genetic characteristics of their ancestors (Anderson & Tushman, 1990; Tellis & Crawford, 1981). Meanwhile, technological search through the Vertical Inheritance pattern is an incremental innovation that inherits and deepens the technological elements of prior technology. This pattern of technological search mainly takes place in the context of an existing dominant design, and technology generates innovation gradually and incrementally based on the dominant design (Lin et al., 2021).

Horizontal gene transfer (HGT) is a pattern in which descendants receive new genetic information from neighboring ancestors in a different lineage than their direct ancestors (Lawrence, 2005; Smets & Barkay, 2005). It is a way of finding new combinations that did not exist before (Carignani et al., 2019), and in biology it occurs primarily by asexual reproduction. This type of search pattern is more readily found in the evolution of technology than biology because technologies have more flexible characteristics and elements than biological genetics (Wagner & Rosen, 2014). There is also a difference in the timing of trait development. In biology, traits inherited by HGT are found immediately in the same generation, whereas in technology, they are found in the next generation, but not in the same. More specifically, in the case of technological evolution, horizontally transferred technological elements influence new technologies in the next generation without causing changes to existing technologies (Cecere et al., 2015; Koski & Kretschmer, 2007).

Mutation (MT) is the appearance of a trait in a descendant that was not observed in the previous generation. This search pattern allows fresh genetic elements to emerge and form new genetic combinations (Kardong, 2005). Mutations in organisms are passed down through the generations as long as they are favorable to survival and reproduction, or at least not significantly disadvantageous. However, above a certain level, it becomes adverse for adaptation to the existing environment, so a high level of mutation is detrimental for survival or fail to leave offspring.

Once a dominant design for a technology has not been established, or a new dominant design needs to be identified, technologies compete to become the dominant design for the next generation (Anderson & Tushman, 1990; Suarez et al., 2015). The winning technologies are those that are differentiated from existing technologies and are derived by introducing new technological elements or finding novel combinations of existing or related technologies (Carignani et al., 2019; Suarez et al., 2015; Wagner & Rosen, 2014). In this case, the former, which introduces a new technological element, is the search pattern of Mutation in the evolutionary phylogenetic tree, and the latter, which finds a novel combination, can be defined as the search pattern of Horizontal Gene Transfer.

To summarize, in an evolutionary context, technological diversity is driven by three patterns of technological search: Vertical Inheritance, which is deepened by inheriting the basic framework from direct ancestors; Horizontal Gene Transfer and Mutation, which introduce genetic traits outside of direct lineage. Moreover, Horizontal Gene Transfer and

Mutation are further segmented by the origin of the heritable traits. HGT involves searching genetic traits in adjacent lineage to find new combinations, while MT implements new genetic traits that did not exist before (Carignani et al., 2019; Kardong, 2005). The evolutionary approach of categorizing technological search into VI, HGT, and MT, allow for an explanation of the scope, direction, and path-dependency of technological search on the nature of technology (and technological element).

5.2 Methodology

5.2.1 Data

The data used for the empirical analysis in this chapter is the same as in Chapter 4. 8,081 granted photovoltaic patents were collected from the United States Patent and Trademark Office (USPTO) database for the period of 2000 to 2018, and 319 sub-group IPC codes for 12 main-group IPC codes were used.

5.2.2 Operational Definition and Modeling of Search

This study defines the technological search as the behavior of combining IPC codes from patents in a technology taxon. There are three search patterns classified according to, where the recombinant IPC code is from (Carignani et al., 2019).

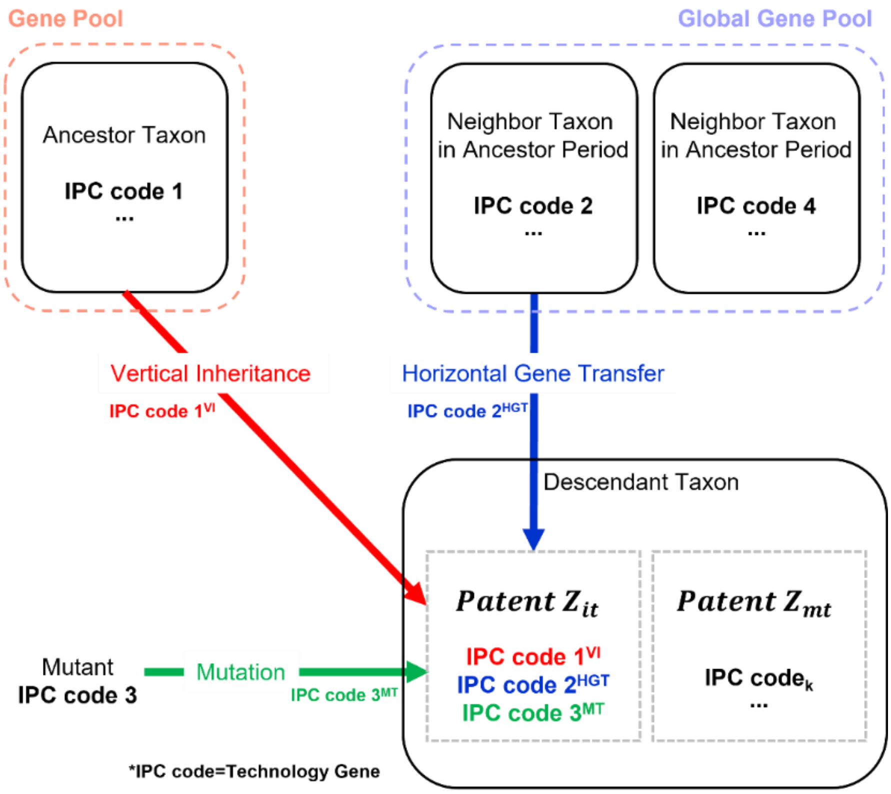


Figure 5-1. Search pattern in the phylogenetic tree of technology

As shown in **Figure 5-1**, patterns of technological search is measured quantitatively by deriving possible ordered pairs of combination between the IPC codes of Patent Z_{it} and Patent Z_{mt} in the same technology taxon. The cases in which the IPC code of Z_{it} is inherited from a direct ancestor or a neighboring ancestor on the phylogenetic tree are defined as Vertical Inheritance (VI) or Horizontal Gene Transfer (HGT), respectively. If a completely new IPC code appears, it is defined as a Mutation (MT).

Prior to measuring searches, we set up a weighted network, defined as a gene pool, with IPC codes as nodes, and the relatedness between them as links (**Equation (5-1)**). This is because in forming IPC code-ordered pairs between patents, the heterogeneous relatedness and complexity of the space should be considered (Song et al., 2019).

$$Gene\ Pool(V, E) \qquad \text{Eq. (5-1)}$$

$$V = \{IPC\ code_1, IPC\ code_2, IPC\ code_3, \cdots\}$$

$$E = \{e_{kl} | \sum_{Z_{mt}} \delta_m(IPC\ code_k, IPC\ code_l)\}$$

$$Relatedness(\boldsymbol{\varphi_{kl}}) = \frac{Link\ weight\ between\ IPC\ code_k\ and\ IPC\ code_l}{Sum\ of\ total\ link\ weight\ in\ Gene\ Pool}$$

$$Complexity(Gene\ Pool) = \frac{Number\ of\ Actural\ Links\ in\ Gene\ Pool}{Number\ of\ Possible\ Links\ in\ Gene\ Pool}$$

$\delta_m(IPC\ code_k, IPC\ code_l)$ is a co-occurrence function and has a value of 1 if patent Z_{mt} simultaneously has both $IPC\ code_k$ and $IPC\ code_l$, and 0 otherwise. Therefore, the gene pool has a higher link weight when different IPC codes are technologically related, and emerge concurrently in many patents. The relatedness $\boldsymbol{\varphi_{kl}}$ is defined as the link weight between the two IPC codes for the total in the gene pool. In addition, the spatial complexity of the gene pool is measured by network density, which is the number of links formed divided by the number of all possible links. The more complex the network, the more links it has and the higher its value (Furht, 2010).

Operational definitions for the three search patterns are as follows.

$$\Phi_j = \text{Ancestor Taxon of } C_{jt} \qquad \text{Eq. (5-2)}$$

$$Gene\ Pool(V, E), V \in \Phi_j$$

$$IPC\ code^{VI} = \{IPC\ code | IPC\ code \in\ Z_{it}\ \ and\ IPC\ code \in \Phi_j\ \}$$

$$\boldsymbol{VI\ Search}\ (Z_{it}) = \frac{\sum_{IPC\ code_k^{VI}} \sum_{Z_{mt} \in C_{jt}, Z_{mt} \neq Z_{it}} (\sum_{IPC\ code_l \in Z_{mt}} y_i^{VI} \boldsymbol{\varphi_{kl}^{\Phi_j}} y_m)}{Complexity(Gene\ Pool)}$$

$$y_i^{VI} = \frac{1}{Number\ of\ IPC\ code^{VI}\ \ in\ Z_{it}}$$

$$y_m = \frac{1}{Number\ of\ IPC\ code\ \ in\ Z_{mt}}$$

Equation (5-2) shows the Vertical Inheritance (VI) search for patent Z_{it}. The gene pool was constructed using the IPC codes of the direct ancestor (Φ_j) of taxon C_{jt} where Z_{it} exists. VI search is measured by counting IPC codes inherited from the direct ancestors ($IPC\ Code^{VI}$) and IPC code combinations that can form with other patents Z_{mt} existing in the same taxon C_{jt} ($IPC\ code_k^{VI}, IPC\ code_l$). For each pair, the relatedness $\boldsymbol{\varphi_{kl}^{Gene\ Pool}}$ and share of each IPC code in each patent (y_i^{VI}, y_m) are given as weights. Lastly, the more complex the gene pool, the more difficult it is to search; therefore, it is divided according to the complexity of the gene pool.

Φ_j^c = Neighbor Ancestor Taxa of C_{jt} Eq. (5-3)

$$Global\ Gene\ Pool(V, E), V \in \Phi_j^c$$

$$IPC\ code^{HGT} = \{IPC\ code | IPC\ code \in\ Z_{it}, \Phi_j^c\ \ and\ IPC\ code \notin \Phi_j\ \}$$

$$\boldsymbol{HGT\ Search}\ (Z_{it}) = \frac{\sum_{\boldsymbol{IPC\ code_k^{HGT}}} \sum_{Z_{mt} \in C_{jt}, Z_{mt} \neq Z_{it}} (\sum_{\boldsymbol{IPC\ code_l \in Z_{mt}}} \boldsymbol{y_i^{HGT}} \boldsymbol{\varphi_{kl}^{\Phi_j^c}} \boldsymbol{y_m})}{Complexity(Global\ Gene\ Pool)}$$

$$y_i^{HGT} = \frac{1}{Number\ of\ IPC\ code^{HGT}\ \ in\ Z_{it}}$$

$$y_m = \frac{1}{Number\ of\ IPC\ code\ \ in\ Z_{mt}}$$

Equation (5-3) shows the Horizontal Gene Transfer (HGT) search for patent Z_{it}. There were two differences between HGT and VI. The first is that HGT uses a global gene pool that excludes the direct ancestor (Φ_j^c), and the other is the IPC code of Z_{it}, which exists in the prior generation but does not exist in the direct ancestor ($IPC\ code^{HGT}$).

Eq. (5-4)

$$IPC\ code^{MT} = \{IPC\ code | IPC\ code \in\ Z_{it}\ \ and\ IPC\ code \notin \Phi_j, \Phi_j^c\ \}$$

$$\boldsymbol{MT\ Search}\ (Z_{it}) = \frac{\sum_{IPC\ code_k^{MT}} \sum_{Z_{mt} \in C_{jt}, Z_{mt} \neq Z_{it}} (\sum_{IPC\ code_l\ \in Z_{mt}} y_i^{MT} \varphi_{kl}^{\Phi_j^c} y_m)}{Complexity(Global\ Gene\ Pool)}$$

$$y_i^{MT} = \frac{1}{Number\ of\ IPC\ code^{MT}\ \ in\ Z_{it}}$$

$$y_m = \frac{1}{Number\ of\ IPC\ code\ \ in\ Z_{mt}}$$

Equation (5-4) shows the mutation (MT) search for patent Z_{it}. The global gene pool is used for MT, similar to HGT; however, the IPC code of Z_{it} has not existed before ($IPC\ code^{MT}$).

In addition, there are cases where IPC code pairs that are combined exist in the gene pool but do not form a link. There are also cases where the same IPC code pairs existing in different patents are combined. In the first case, although it has never had a technological combination, we considered it to be in the gene pool as a candidate for a combination, and relatedness was calculated by assigning the minimum value of technological relevance in the gene pool. In the second case, the maximum value of technological relevance within the same gene pool was used as the relatedness value.

Finally, to measure the search in each trajectory, the value of individual patents was measured using **Equation (5-2), (5-3),** and **(5-4),** and an average value was then derived as **Equation (5-5)**.

$$Search(C_{jt}) = \frac{\sum_{Z_{it} \in C_{jt}} Search\ (Z_{it})}{Number\ of\ patents\ in\ C_{jt}} \qquad \text{Eq. (5-5)}$$

5.2.3 Regression Analysis

Technological diversity changes depending on the elements of the technology that are explored (Carignani et al., 2019; Song et al., 2019). If a dominant design is formed in an industry, technology pursues incremental innovation (Lin et al., 2021), which is a gradual innovation pattern that inherits and deepens the technology of direct ancestors (VI). Thus, under these conditions, technological diversity stagnates or diminishes (Anderson & Tushman, 1990; Suarez et al., 2015).

However, when a dominant design is not formed, or a new dominant design needs to be created, technologies compete to produce the dominant design of the next era (Anderson & Tushman, 1990; Suarez et al., 2015). The dominant design is a technology that differs from existing technologies. Therefore, it is derived by introducing an innovation that is not in the existing technology (MT) or by finding a new combination of related technologies (HGT). In this case, the technological diversity in existing industries increases with new combinations (Carignani et al., 2019; Wagner and Rosen, 2014).

Regression analysis is conducted to quantitatively verify the mechanism of diversity dynamics. The dependent variable in the regression model is the entropy of taxon representing the technological diversity, whereas the explanatory variables are three patterns of technological search: VI, HGT, and MT. In addition, gene pool size, global gene pool size, and the total number of patents in the taxon are used as control variables.

As demonstrated in **Equation (5-6)**, a mixed regression model was constructed with technological search as a fixted effect and year as a random effect. The purpose of a mixed regression model is to reflect the influence of exogeneous factors that may exist between years in the analysis of longitudinal data (Faraway, 2016).

$$TD_{jt} = \beta_0 + \beta_1 VI_{jt} + \beta_2 HGT_{jt} + \beta_3 MT_{jt} + \sum_k \beta_k \, Control\, Variables_k + \gamma_0^t + \varepsilon_{jt} \qquad \text{Eq. (5-6)}$$

Where, j is the index of the taxon, t is the year of each taxon, and ε is an error term. γ_0^t is the random effect of year t. The definition of variables is listed in **Table 5-1**.

Table 5-1. Definition of variables

Variables		Description	Proxy
Dependent Variable	TD_{jt}	Entropy of Taxon	Technological diversity
Independent Variables	VI_{jt}	Vertical Inheritance of Taxon	The degree of search
	HGT_{jt}	Horizontal Gene Transfer of Taxon	
	MT_{jt}	Mutation of Taxon	
Control Variables	$\sum_k \beta_k \, Control\, Variables_k$	Gene Pool Size Global Gene Pool Size Number of patents in Taxon	-

5.3 Technological Search as the Driver of Diversity Dynamics

5.3.1 Changes of Search Patterns on Evolutionary Trajectories

In this section, we observe the dynamics of search for the major technological trajectories that evolve from root to [2018_1], [2018_2], and [2018_3]. Each trajectory represents the first-generation ([2018_2]), the mixture of first and second-generation ([2018_1]), and third-generation ([2018_3]) technologies existing in 2018. To demonstrate the relationship with technological diversity, this section presents the diversity dynamics resulted from **Chapter 4**, along with the search patterns for each trajectory. The time-varying measures of technological diversity and search across the three trajectories are shown below[33].

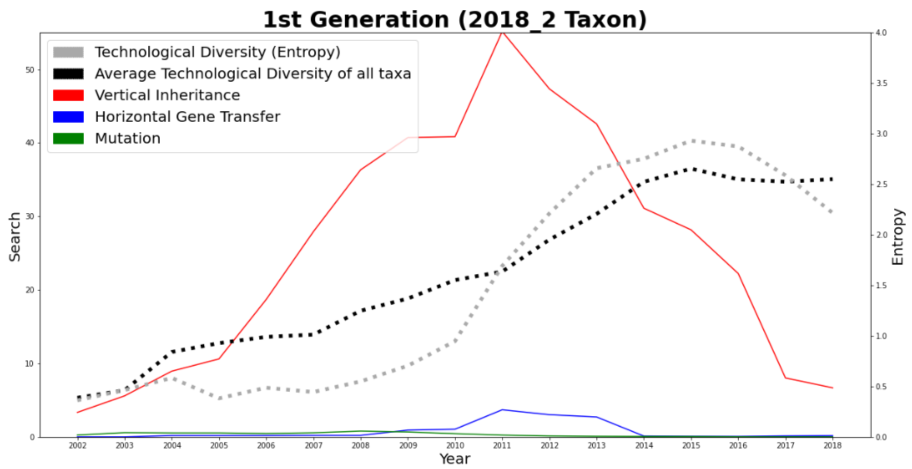


Figure 5-2. Diversity and search in 1st generation (Root – 2018_2 taxon) over time

[33] The result is applied the 3 Simple Moving Average method to express a smooth trend.

Figure 5-2 shows the results of the [2018_2] trajectory, representing the evolution of first-generation technologies. The black dotted line represents the average change in diversity of all taxa in the phylogenetic tree. The grey dotted line represents the diversity of the [2018_2] trajectory. In the case of first-generation technology, diversity was lower than the average of all technologies before 2011 and showed a stagnant trend without a significant increase. This is because VI was the dominant search in this trajectory until 2011, which is related to the dominant design of Al-BSF cells. However, the diversity shows rapid growth after 2011, which is due to the discovery of new technological combinations through HGT in the late 2000s during the industrial slump. Recently, VI has reduced, and HGT and MT have not occurred in this trajectory with the diversity of first-generation technologies decreasing since 2015. In other words, in the case of first-generation technology, technological diversity should be promoted by trying new technology combinations utilizing other technologies.

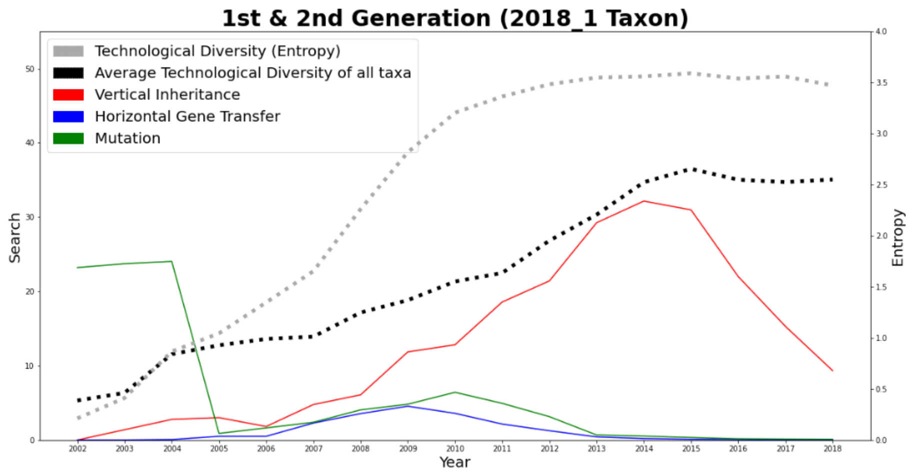


Figure 5-3. Diversity and search in 1st & 2nd generation (Root – 2018_1 taxon) over time

Figure 5-3 shows the trajectory from Root to the [2018_1] Taxon, which consists of a mix of first and second-generation technologies. In the case of the trajectory, with the exception of the early 2000s, the diversity was higher than the average for photovoltaic technology. In addition, compared to the first-generation technology, which was mostly VI, it showed a high level of MT at first, and both HGT and MT occurred steadily until the early 2010s. This implies that unlike first-generation technologies, technological development began with the introduction of new technologies and continued until the early 2010s, through constant searching for new combinations of technologies.

Historically, to implement lab-scale technology for industrial use, first-generation technology has applied second-generation technology. In particular, as the thickness and size of wafers becomes thinner and larger, the formation of thin-film for surface passivation has become increasingly important. This is reflected in the patterns of the MT and HGT in the trajectory.

In 2018, however, the diversity in this trajectory was stagnant at a high level. This is because of competitions between various technologies and the market selection to derive the new dominant technology design (Anderson & Tushman, 1990; Lin et al., 2021). Therefore, for first and second-generation mixed technologies, now is the time to focus on deriving a new dominant design by deepening the existing technology through VI, rather than seeking additional improvement in diversity.

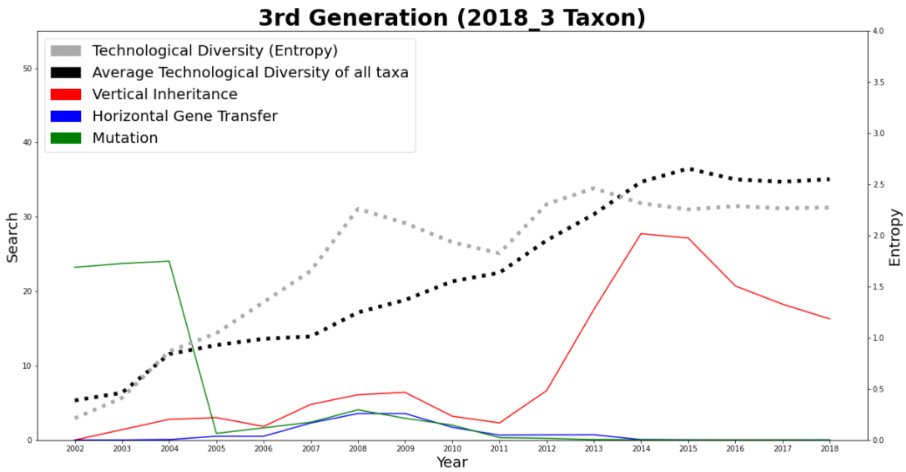


Figure 5-4. Diversity and search in 3rd generation (Root – 2018_3 taxon) over time

Figure 5-4 shows the trajectory of [2018_3] composed of third-generation technologies. This trajectory was the same as that of [2018_1], but after speciation in 2008, technological diversity showed decreasing and stagnating patterns. The third-generation technology describes similar patterns of diversity as the first and second-generation mixture technologies, that is, a stagnant trend. However, it remains at a lower level than the average for photovoltaic technological diversity. Therefore, the current mission of third-generation technology is to enhance technological diversity through the introduction and combination of new technologies.

In this section, it is confirmed that the dynamics on diversity and search patterns observed in the major trajectories of evolutionary phylogenetic tree corresponds well to the developmental history of first-, second-, and third-generation photovoltaic technologies. Therefore, the results validate the appropriateness of the measures proposed in this study.

5.3.2 Relation between Diversity Dynamics and Technological Search

In this section, the mechanism of diversity dynamics for searching is revealed through the results of the regression model constructed in **Section 5.2.3**.

Table 5-2. Descriptive summary and correlation coefficients for variables

Variable	Obs	Mean	S.D.	1.	2.	3.	4.	5.	6.	7.
TD_{jt}	103	1.69	1.07	1.00	0.29	0.10	-0.10	0.69	0.55	0.69
VI_{jt}	103	11.49	14.42		1.00	0.21	-0.13	0.16	0.29	0.60
HGT_{jt}	103	0.66	1.78			1.00	0.37	-0.15	-0.15	0.048
MT_{jt}	103	1.85	7.94				1.00	-0.13	-0.24	-0.086
Gene Pool Size	103	26.04	33.08					1.00	0.40	0.67
Global Gene Pool Size	103	65.41	49.22						1.00	0.37
Number of patents in Taxon	103	59.43	82.62							1.00

Table 5-2 presents the basic statistics and correlation coefficients of the variables. An interesting fact found in **Table 5-2** is that HGT is the least common search method in photovoltaic technology. This implies that photovoltaic technologies have developed

mainly by deepening existing technologies (VI) or introducing new technologies (MT), not present in previous trajectories, while innovation through convergence of existing trajectories is lacking.

The correlation analysis between the variables shows that the explanatory variables VI, HGT, and MT have low correlation coefficients of 0.4 or less, indicating that there is no multicollinearity problem. However, for the control variables, such as size, we observe that their correlation with other variables is higher than 0.6. To check whether this level of correlation could introduce error into the regression analysis, a variance inflation factor (VIF) analysis is performed. VIF analysis is a method of measuring the level of correlation between variables by performing a regression analysis with a specific variable as the dependent variable and the remaining variables as explanatory variables.

Table 5-3. Result of variance inflation factor analysis

Variable	VIF
Intercept	1.000
Entropy	3.202
VI	2.230
HGT	1.474
MT	1.260
Gene_pool_size	2.726
Global_Gene_pool_size	1.696
Size	3.420

The results of VIF analysis are described in **Table 5-3**. The Size variable has the highest VIF value of 3.420. Generally, a VIF value of less than 10 is considered to be free of multicollinearity issues; therefore, multicollinearity is not an issue in this study.

Table 5-4. Results of the regression

Dependent variable: Entropy	Model 1	Model 2	Model 3	Model 4
Intercept	-0.00 (0.082)	-0.00 (0.082)	-0.00 (0.084)	-0.01 (0.085)
Vertical Inheritance of Taxon	-0.15 (0.081)	-	-	**-0.22** (0.077)**
Horizontal Gene Transfer of Taxon	-	**0.20*** (0.058)**	-	**0.24*** (0.060)**
Mutation of Taxon	-	-	0.066 (0.065)	-0.020 (0.064)
Gene Pool Size	**0.26** (0.091)**	**0.38*** (0.080)**	**0.33*** (0.083)**	**0.28*** (0.054)**
Global Gene Pool Size	**0.31*** (0.079)**	**0.31*** (0.078)**	**0.29*** (0.081)**	**0.35*** (0.081)**
Number of patents in Taxon	**0.52*** (0.10)**	**0.33*** (0.077)**	**0.39*** (0.080)**	**0.51*** (0.096)**
Number of Obs.	103	103	103	103
Likelihood	-99.35	-95.68	-100.77	-95.32

Notes:
1. Standard errors are in parentheses.
2. ***, **, and *denote statistical significance at the 0.1%, 1%, and 5%levels, respectively.
3. bold denote statistical significance at the 0.1%, 1%, and 5%levels

Table 5-4 presents the results of the regression analysis. Models 1, 2, and 3 were analyzed by considering only one explanatory variable, VI, HGT, and MT, respectively. Model 4 was analyzed by considering all three explanatory variables. Diversity showed a statistically significant negative (-) relationship with VI, a statistically significant positive (+) relationship with HGT, and no statistically significant relationship with MT. The same result was derived from Model 4, which analyzed all three searches by integration.

According to the results, VI search reduced the diversity level. Because VI is a gradual innovation pattern that selects superiority among various technologies and passes them on to the next generation, it only maintains and improves the technological composition of the ancestors.

However, HGT searches increase diversity. In Models 2 and 4, the HGT showed a statistical significance level of 0.1%. This result emphasizes the importance of combinatorial innovation, which finds new combinations of existing technologies in the same industry but in different trajectories.

Interestingly, MT search had no significant effect on enhancing diversity. The results imply that the introduction of new technology, not previously active in the industry, does not “immediately” affect technological diversity. Specifically, a new technology does not affect diversity by simply being introduced. However, after being introduced, it survives in the technology space and affects diversity through VI based on direct ancestors or HGT based on neighboring ancestors.

The results of the control variable showed that the greater the genetic pool of ancestors, that is, the technology space whether direct or neighboring, the higher the diversity level of descendants. This is because the greater the space for searching for diverse technologies, the greater the possibility of generating various combinations.

The robustness of the mixed effects regressions presented in this chapter is checked by adding both period dummy variables and the interaction terms between period and technological search in pooled ordinary least squares (OLS). The robustness checks show that even with the heterogeneous effects of year, the effects of VI, HGT, and MT's technology search patterns on technology diversity are consistent with the original model. In addition, the interaction of period and technological search is not significantly related to technological diversity. This suggests that the relationship between diversity and technological search derived from this study is independent of the effects of time of year, such as the life cycle of an industry or technology and is an endogenous determinant of technological diversity unaffected by exogenous changes. Details of the robustness checks are provided in Appendix I.

To summarize, technological diversity is affected by the patterns of technological search, and the level of diversity in descendants is proportional to the genetic space of their ancestors. Search by vertical inheritance patterns reduces the level of diversity while search by horizontal gene transfer patterns increases it. In addition, search by mutation patterns has no significant effect. These results are independent of time or external effects, indicating that technological search is an internal driver of technological diversity. The results suggest that the search for new combinations of technologies, leveraging new technological elements from neighboring ancestors that can be identified through technological phylogenetic tree, is the principle of increasing technological diversity.

5.4 Sub-conclusion

This study investigates the diversity dynamics of photovoltaic technology on technological search from an evolutionary perspective. Three search patterns, namely vertical inheritance (VI), horizontal gene transfer (HGT), and mutation (MT), were hypothesized as drivers of diversity dynamics and empirically tested on an evolutionary phylogenetic tree.

To this end, a dataset of 8,081 photovoltaic technology patents filed and granted with the US Patent and Trademark Office (USPTO) from 2000 to 2018 is constructed, and the IPC code of the patents is used as a proxy for photovoltaic technology. In addition, this study proposes quantitative measures of technology diversity and technological search patterns along the photovoltaic technology phylogenetic tree. The relationship between diversity dynamics and technological search is derived through regression analysis. The results are summarized as follows:

First, VI is the main search pattern in photovoltaic technology, while HGT is minor. This means that photovoltaic technology has mainly pursued gradual innovation within the technology trajectory formed by the sub-technology itself. Correspondingly, there has been a lack of innovation in trying to find new technology combinations through convergence between existing sub-technologies.

Second, the results of the regression analysis show that VI decreases the level of diversity, while HGT increases it. This implies that in order to promote technological diversity, a new combination of technologies should be developed using relevant technologies in the industry. In addition, MT has a statistically insignificant effect on diversity. In other words, a newly introduced technology in the technology space should first survive and then affect diversity through VI and HGT. The results of the control variables confirm that the greater the technological range of ancestors, whether immediate or neighbors, the higher the level of diversity in their descendants. Furthermore, the relationship between technological diversity and technological search patterns is independent of temporal or external factors.

Figure. 5-5 summarizes the result on the dynamic mechanism of technological diversity. Technological diversity increases significantly with the recombination of technologies from neighboring ancestors that can be identified in the evolutionary phylogenetic tree of technology.

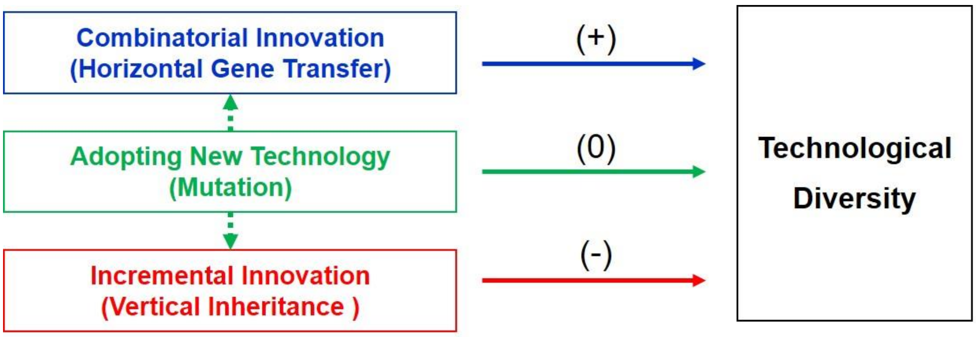


Figure 5-5. The mechanism of diversity dynamics on technological search

In the case of photovoltaic technology, governments have recognized that demand-driven policies in the early 2000s led to the technological lock-in of crystalline silicon photovoltaic cells and are working to reduce barriers between technologies to overcome current technological challenges (e.g., Shockley-Queisser limit[34]). For example, the photovoltaic cell part of South Korea's "Alchemist" project, which previously presented research challenges in technology groups such as crystalline silicon photovoltaic cells or thin-film photovoltaic cells[35], now presents end goals such as "solar cells that overcome the theoretical limit efficiency of 35% or more" or "glass window-type transparent solar cells" without detailed technological restrictions. This indicates a willingness to allow technological convergence and innovation. This technological inclusiveness is expected to lead to an increase in technological diversity.

The finding in this chapter points to a strategic approach for success in such endeavor: the principle of generating technological diversity identified in this study is to recombine with other technologies within the scope of technological relevance and gradually expand the space for evolution. Therefore, the direction for photovoltaic technology to expand technological possibilities beyond the existing barriers and for further development is to create combinatorial innovation through recombination within the range of accumulated technologies in the photovoltaic space. Specific proposals for this are discussed in Chapter 7.

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[34] Also known as the radiative efficiency limit in physics. It is the maximum theoretical efficiency of a photovoltaic cell with a single p-n junction.
[35] For example, the new task of the Climate Change Response Technology Development Project in 2015 is "Development of non-silicon-based next-generation thin-film solar cell source technology."

Chapter 6. Organizational Routine to the Diversity Dynamics of Technology

6.1 Derivation of Organizational Routine by Multi-dimensional Behaviors

At the micro level of the economy, differences are observed in each of the various dimensions that describe firms such as size, age, structure, strategy, and performance (Hoopes & Madsen, 2008; Rumelt et al., 1994). In other words, firms are heterogeneous, and they react differently to the same situations and conditions and are differentially affected by change (Becker & Knudsen, 2017; Kirman, 1992). Firm heterogeneity[36] has significant implications for the change and development of social, economic, and innovation systems (Hoopes & Madsen, 2008; Nelson, 1991a; Nelson, 1995; Wagner, 2011).

Technology is as a recipe. The same technology (or technology elements) can produce different results depending on the recipe, which in tern relies on the actor's ability to execute the recipe (Baldwin & Clark, 2000; Dosi & Nelson, 2010). Firms with their own routines behave differently and generate performance based on bounded rationality. Consequently, heterogeneity persists in an economy as well as technological diversity generates (Dosi & Nelson, 2010).

---

[36] Heterogeneity in evolutionary economics refers to the state in which differences exist within a group (Nelson, 1991b, 2007; Saviotti, 1991).

From the evolutionary economics perspective, the firm theory uses a firm's organizational routine, not the firm itself, as the basic unit for understanding the firm[37]. Routines are repetitive patterns of organizational behavior (Dosi et al., 2000; Feldman & Pentland, 2003; Geels, 2014; Nelson & Winter, 1982; Winter, 1988). Heterogeneous firm and its behavior to generate technological diversity is explained by its routine, and can be understood through its routine and how it changes over time (Dosi & Nelson, 2010). Therefore, identifying firm heterogeneity and the organizational routines underlying it is a prerequisite to understanding the mechanisms of technological diversity dynamics for actors.

Evolutionary economics considers routine through the lens of capabilities (Baldessarelli et al., 2022; Parmigiani & Howard-Grenville, 2011). Routines are a type of black-box entity that runs in the subconscious realm of a firm and leads to tangible results (Cohen & Bacdayan, 1994; Dosi et al., 2000; Nelson, 1995). Scholars have built a theoretical foundation for routines in terms of "what" and "why," and explored the impact of routines on firms' performance (Baldessarelli et al., 2022; Pharmigiani & Howard-Grenville, 2011). However, to the best of our knowledge, few studies have directly measured and identified the routines of individual firms. The difficulty of empirical research on routines is that routine is a concept with a high level of complexity in an abstract form that is latent in the

[37] In evolutionary economics, the firm theory is the dynamic research of the generation, growth, and extinction of heterogeneous firms. Through a non-reductional approach, firms, which are goal-oriented organizations, are considered distinct from individuals (Herrmann-Pillath, 2002). Evolutionary economics considers the actual and observable behavior of firms, and places technological and organizational innovation at the center (Winter, 1988).

firm. This makes it difficult to construct a database for empirical analysis and define basic empirical operations such as comparisons (Pentland et al., 2010).

Based on the proposed concept of routines in **Figure 2-1**, this study uses observable firm behavior as data for empirical research on routine. Then, with two major originalities, we quantify and categorize innovation routines to present a qualitative indicator of firm heterogeneity. The first is a multidimensional approach to routines, as they have a high level of complexity in producing satisfactory performance (Cattani & Malerba, 2021). Recent economic studies have embraced a multidimensional approach to explain the complexity inherent in socioeconomic phenomena (Stojkoski et al., 2023). In addition, integrated results are derived by combining various data on economic activities, such as transactions (trade data), technology development (patent data), and production (product data) (Stojkoski et al., 2023). This study adopts a two-dimensional approach to a firm's *Knowing* and *Doing* to quantitatively measure an innovation routine, and uses patent and product data, respectively.

The key conceptual advantage of routine research is that it links the competitive dynamics of an industry with the nature of the firm-level processes of search and adaptation (Cattani & Malerba, 2021; Gavetti & Levinthal, 2004). Routines have context-specificity (Cohen et al., 1996; Pisano & Teece, 1994; Teece et al., 1997); therefore, it is necessary to consider the sectoral regime to connect routines and industrial dynamics, because there is a firm-level routine for an industry in a homogenous environment. The second is to measure organizational routines using the concepts of exploration and exploitation in each dimension of *Knowing* and *Doing*, and to compare them relatively within the sectoral regime. Specifically, a firm's willingness for novelty[38] was identified as an indicator of exploration and exploitation, and innovation routines were classified into four types through a relative comparison between firms: active pioneers, efficient optimizers, adaptive adventurers, and passive observers.

6.2 Research Framework to Identify Organizational Routines

6.2.1 Innovation Routine via Innovation Behaviors: *Knowing* and *Doing*

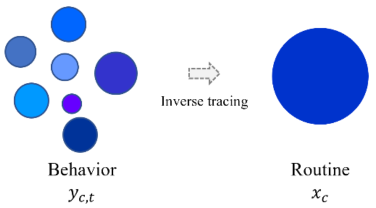
The routine to be identified in this study is limited to a firm's innovation routine. Based on Schumpeter's definition of innovation as "the realization of a new union"[39] (Schumpeter, 1911; 159) the innovation routine is defined as a recurrent behavioral pattern for an organization to realize a new combination. As the routine inherent in a firm does not appear on the surface, it is approached through the observable behavior of a firm derived from the routine.

Based on the concept of routine presented in **Figure 2-1**, this study derives the routine $\boldsymbol{x_c}$ by taking the inverse of the behavior of firm c at time t, $\boldsymbol{y_{c,t}}$ (**Figure 6-1**). Specifically,

[38] This term is based on Schumpeter's definition of innovation, that is the realization of a new combination (Schumpeter, 1934).

[39] The definition of innovation as a new combination is generally known as Schumpeter's theory although its basic idea is much older. Adam Smith describes those engaged in what we today call R&D&I as "often capable of combining together the powers of the most distant and dissimilar objects (Smith 1976; I.i.9)". Marx also explicitly used the expression "new combination" (Marx, 1959;255) in Das Kapital (1959)'s discussion of the role of technological progress (Kurz, 2012).

the firm's innovation routine $x_c^{Innovation}$ is derived from its behavior to generate a new technological combination, $y_{c,t}^{Innovation}$.



$$f_t(x_c) = y_{c,t} \xrightarrow{Inverse} f_t^{-1}(y_{c,t}) = x_c$$

For deriving the innovation routine of firm c,

$$f_t^{-1}\left(y_{c,t}^{Innovation}\right) = x_c^{Innovation}$$

where, $x_c^{Innovation}$: Innovation Routine of firm c

$y_{c,t}^{Innovation}$: Behavior of firm c for generating a new combination in technologies at time t

Figure 6-1. Identification of innovation routines through behavior

A firm's innovation behavior is divided into *Knowing* and *Doing*. In this study, *Knowing* is a behavior for what to know, and is an innovation in technology development. *Doing*' is a behavior for what to do, and is an implementation of technological innovation through product development. The innovation routine of a firm is expressed in two dimensions, *Knowing* and *Doing*, as in the following formula in **Equation (6-1)**:

Innovation = (Knowing, Doing) Eq. (6-1)

$$x_c^{Innovation} = \left(\left[f_t^{-1}\left(y_{c,t}^{Knowing}\right)\right], \left[f_t^{-1}\left(y_{c,t}^{Doing}\right)\right]\right)$$

$$= \left(x_c^{Knowing}, x_c^{Doing}\right)$$

$$\therefore\ x_c^{Innovation} = \left(x_c^{Knowing}, x_c^{Doing}\right)$$

6.2.2 Measuring the Willingness for Novelty: Exploration and Exploitation

This study observes a firm's willingness for novelty in generating new technological combinations to derive innovation routines from *Knowing* and *Doing*. The degree of willingness for novelty uses the concepts of exploration and exploitation as indicators.

The continuous survival and growth of a firm depend on its ability to explore new possibilities and exploit old certainties (Kuran, 1988; March, 1991). Specifically, a firm's innovation activities are the result of choosing either the "exploration" of opportunities through new knowledge or technology in a future-oriented way, or the "exploitation" of existing knowledge, products, and services based on the past (Farjoun, 2010; Smith et al., 2010).

The concepts and mechanisms of exploration and exploitation were presented by March (1991) in the field of organizational theory. He provided various concepts related to exploration and exploitation and broadly defined them. Exploration was described by him as search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation. And is the "pursuit of new knowledge," Exploration is an activity in which a firm expands its future competencies by adding external novelty to knowledge, resources, and capabilities (Nooteboom, 2000), and searching for unfamiliar spaces (Cattani & Malerba, 2021).

On the other hand, exploitation is the "use of the already known," such as refinement, choice, production, efficiency, selection, implementation, and execution (March, 1991).

Exploitation is an activity that refines existing capabilities, technologies, and paradigms by recombining existing ones or adding existing and external ones (Nooteboom, 2000), and searching for spaces already known to innovators (Cattani & Malerba, 2021).

Therefore, the concepts of exploration and exploitation are comprehensive. As a result, exploration and exploitation are used in various fields such as technological innovation, management strategy, and organizational learning (e.g., Auh & Menguc, 2005; Benner & Tushman, 2003; Bierly & Daly, 2007). **Table 6-1** summarizes some of the concepts of exploration and exploitation defined in previous studies.

Table 6-1. Definition of exploration and exploitation

Articles	Exploration	Exploitation
Benner & Tushman, 2003	radical innovations or those for emergent customers or markets are exploratory, since they require new knowledge or departures from existing skills	incremental technological innovations and innovations designed to meet the need of existing customers are exploitative and build upon existing organizational knowledge.
He & Wong, 2004	technological innovation activities aimed at entering new product-market domains	technological innovation activities aimed at improving existing product-market positions
Rothaermel & Deeds, 2004	exploration alliances are entered into with the motivation to discover something new; they focus on the 'R' in the research and development process	exploitation alliances focus on the 'D' in the R&D and are entered into with the goal to join existing competencies across organizational boundaries to make synergies
Auh & Menguc, 2005	exploration is concerned with challenging existing ideas with innovative and entrepreneurial concepts	exploitation is chiefly interested in refining and extending existing skills and capabilities
Lavie & Rosenkopf, 2006	search, variation, risk taking, experimentation, play, flexibility, discovery, innovation	refinement, choice, production, efficiency, selection, implementation, execution
Bierly & Daly, 2007	the creation or acquisition of new knowledge	the ability to leverage existing knowledge to create new organizational products and processes
Lin et al., 2007	adaptation(exploration) attaches importance to adaptive mechanisms that call for experimentation, variation, search, and innovation	alignment(exploitation) enables firms to engage in refinement, implementation, efficiency, and production
Bierly et al., 2009	exploration refers to the application of external knowledge to produce new products and technologies	exploitation refers to the application of the external knowledge to refine the organization's existing products and improve its processes

Exploration and exploitation are in a paradoxical relationship, interrelated by an organization's ambidexterity to respond and adapt to environmental change (Benner & Tushman, 2003; Raisch & Zimmermann, 2017; Smith & Lewis, 2011). Recent studies explain that exploration and exploitation are complementary forces that tend to reinforce each other when they occur simultaneously over time (Raisch et al., 2009), but have a trade-off in terms of resources (Cattani & Malerba, 2021; Koryak et al., 2018; Tushman & O'Reilly, 1996), and produce continuous organizational tension (Lubatkin et al., 2006; Smith & Lewis, 2011).

This study uses the concepts of exploration and exploitation as indicators of a firm's willingness for novelty. In other words, exploration and exploitation are located at both ends as complementary substitutes for a firm's innovation behavior. It is defined as a firm with an explorative innovation routine if it is conducted in an unfamiliar space because of its strong willingness for novelty; conversely, it is defined as a firm with an exploitative innovation routine if it is conducted in a familiar space.

6.2.3 Classification of Innovation Routines

Innovation routine is categorized based on the degree of willingness for novelty in the firm's *Knowing* and *Doing* behavior, that is, exploration and exploitation. The firm's innovation routine, expressed in **Equation 6-1**, is classified into a two-dimensional space, with the x-axis representing *Knowing* and the y-axis representing *Doing*. In addition, the degree of willingness for novelty is expressed in exploration and exploitation, and relative comparisons are made between firms.

The innovation routine space, expressed in two dimensions, has four quadrants: “explorative/explorative,” “exploitative/explorative,” “explorative/exploitative,” and “explorative/exploitative” (see **Figure 6-2**). The types of innovation routines were categorized according to each quadrant.

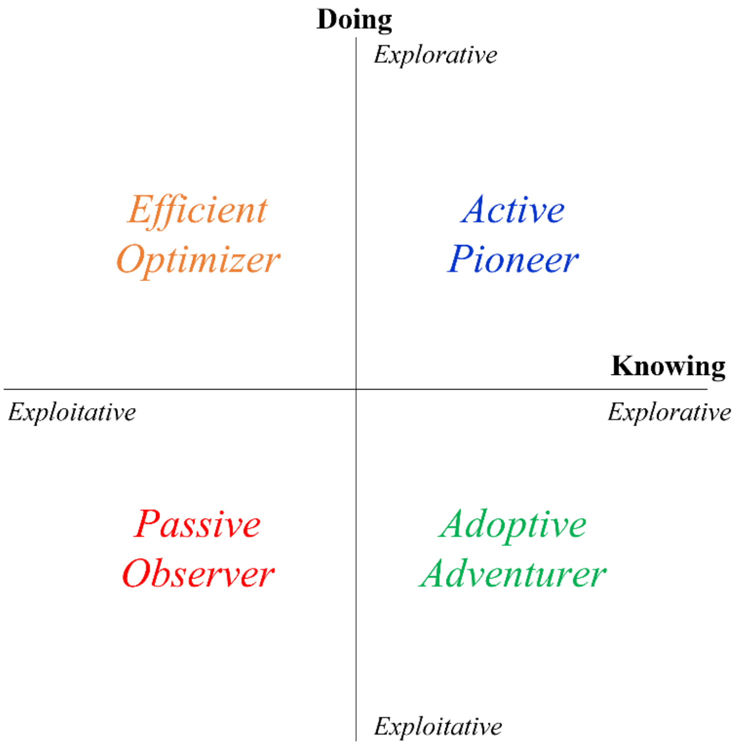


Figure 6-2. Classification of innovation routines

Quadrant 1 is exploratory in terms of both *Knowing* and *Doing*. It is active and challenging, and has a strong will to actively disrupt and change the existing market through innovative efforts. Schumpeter [40] divided economic actors into two types, "energetic-dynamic and hedonic–static," based on their disposition to act (Becker & Knudsen, 2017; Becker et al., 2012)[41]. Quadrant 1 corresponds to Schumpeter's energy-dynamic entrepreneur. They have the disposition of "experiment with something new" (Schumpeter, 1911:162) and are not resistant to change, but rather the obstacles caused by change are given as motivation to promote new combinations (innovation). This study categorizes these firms under the "active pioneer" routine.

The firms in **quadrant 2** are explorative in "Knowing," but exploitative in *Doing.* Firms of this type focus on improving productivity and profitability through process innovation by optimizing existing processes. Alternatively, deep-technology ventures that seek various applications based on the core technology also fall under this category. They have an "efficient optimizer" routine.

The firms in **quadrant 3** are exploitative in both *Knowing* and *Doing.* They are Schumpeter's hedonic-static actors and have the disposition of "essentially do what they have learned" (Schumpeter, 1911: 542). This type has strong internal resistance to change and is motivated by necessity. They moved only within the accepted boundaries and repeated the work performed previously. Their innovation routine is a type of "passive

[40] Schumpeter, 1911: 119, 120, 162, 164, 183, 464, 528, 530, 542-3

[41] "Disposition" is genetically innate, and the same behavioral response occurs in a particular environment. It is a concept distinct from "character" that interacts with and is influenced by the environment (Cloninger, 1987; 1993). According to Cambridge Dictionary, "disposition" means 1) the particular type of character that a person naturally has, and 2) a natural tendency to do something, or to have or develop something, whereas 'character' means the particular combination of qualities in a person or place that makes them different from others.

observer."

Finally, **quadrant 4** includes firms that are explorative in *Knowing* and exploitative in *Doing*. Firms with this routine explore and exploit new opportunities, while balancing risks and rewards. This study classifies those who have various technology portfolios and mainly engage in product innovation as "adaptive adventurer" types.

In summary, this study uses the following structure to firstly quantify and categorize a firm's innovation routines and secondly conduct the relation between technological diversity dynamics and organizational routines (see **Figure 6-3**). The research framework was used to empirically categorize photovoltaic firms. The methodology and results of the analysis are presented in the following sections.

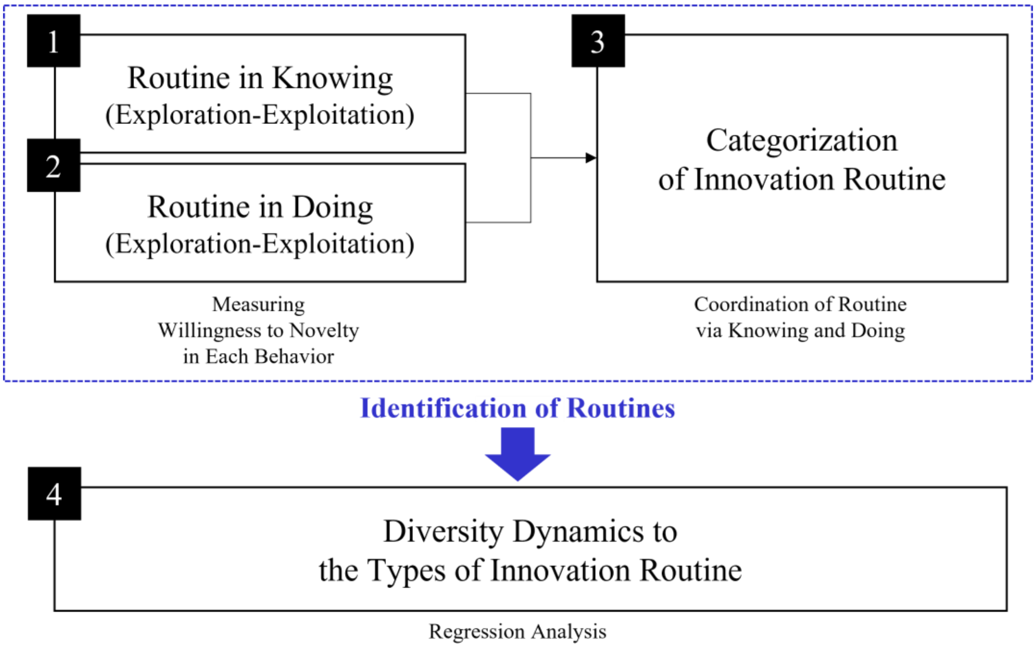


Figure 6-3. Structure of this study

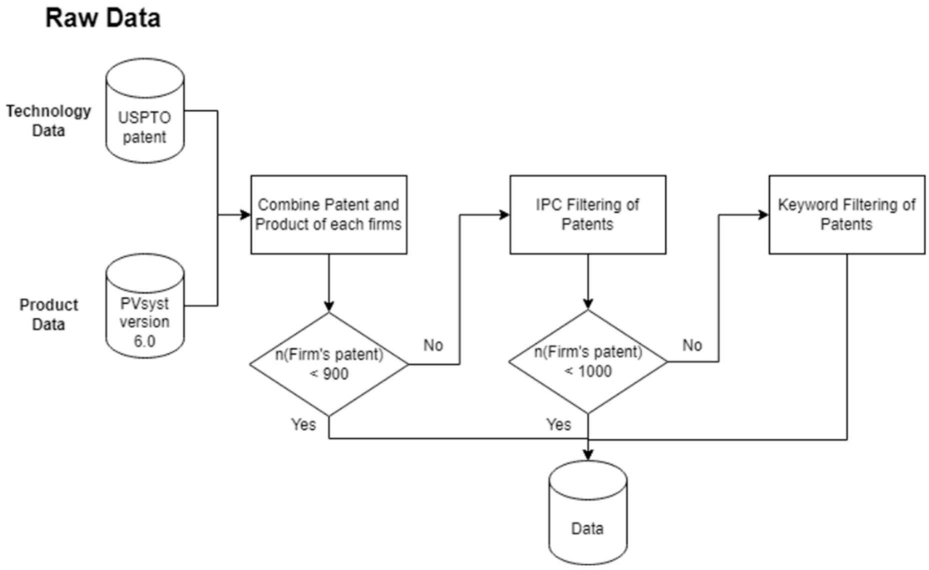
6.3 Methodology

6.3.1 Data

In this study, patent and product data were used as proxies for behaviors for *Knowing* and *Doing* in photovoltaic firms. Patent data are patents granted by the United States Patent and Trademark Office (USPTO), and product data are photovoltaic module data collected using the photovoltaic system design software PVsyst version 6.0. The analysis period was 2000 to 2022, and the targets were photovoltaic firms that launched products and held patents during this period[42].

During the analysis period, 33 photovoltaic firms with both products and patents were identified. Each firm has a considerable difference in the number of patents granted, and the technological scope of each firm's patents also varies significantly. Therefore, to ensure a balanced number of granted patents for each firm, the data were refined as shown in the following way (**Figure 6-4**). First, firms with less than 900 patents used all their granted patents as data, while firms with more than 900 patents were filtered using International Patent Classification (IPC) codes. Firms with more than 1,000 patents even after IPC filtering, such as Samsung, LG, Mitsubishi, and Sharp, were filtered using keywords in the abstract.

[42] Photovoltaic firms were derived by being consolidated and organized patent applicants based on firms in the product data. For example, LG represents all affiliates like LG Electronics, LG Display, etc., and Hanwha includes Q-Cells and Solar One.



Period	2000~2022
IPC Code (Main Group)	H01L21, H01L31, E04D13, H01L27, H02N6, C30B15, C30B29, C30B28, C23C14, C23C16, H01G9, H0IL51
Keywords in Abstract	"solar*" OR "photovoltaic*" OR "solarbatter*" OR "photo-voltaic*" OR "solar batter*" OR "solar-batter*"

Figure 6-4. Data preprocessing flow and search query for patents

As a result of the primary data extraction and refinement, the data of 6,821 patents and 2,408 products were derived for 33 firms. **Table 6-2** shows the top five firms in terms of number of patents and products. Each of the 33 firms exhibited large differences in the number of patents and products. Although some firms have similar numbers of patents and products, most of them show large differences, and the preponderance of patents and products also differs from firm to firm. In other words, by observing the number of patents and products, we can predict the existence of heterogeneous innovation routines.

However, among the 33 firms that were initially drawn, some firms did not have sufficient data for the analysis. After excluding these firms, 19 firms were included in this study. A total of 5,993 patents and 1,094 products were used as the data.

Table 6-2. Top five patent and product for 33 firms

Rank	Firm	# of patents	# of products	Rank	Firm	# of patents	# of products
1	Fuji Electric	856	4	1	CSI solar	1	474
2	SunPower	738	59	2	S-Energy	1	36
3	GE	618	10	3	Solarwatt	4	111
4	LG	613	70	4	Solibro	5	36
5	BP Solar	536	35	5	Calyxo TS Solar	8	22

6.3.2 Measuring Innovation Routines for Each Firm

6.3.2.1 Measuring Routine from *Knowing* behavior

In this section, the behavior of a firm in terms of *Knowing*–that is, the routine of innovation activities for technology development–is quantitatively measured. In this study, the process through which each firm builds its own patent network is defined as innovation activity for *Knowing*. Specifically, each firm's routine was quantitatively measured by observing the process of establishing a network of patents registered with the USPTO. The patent network ($\boldsymbol{G_{c,t}}$) of a specific firm c at time t is defined as **Equation (6-2)**.

$$G_{c,t} = (V, E) \quad \text{Eq. (6-2)}$$

$$V = \{v |\ v \in Granted\ Patent\ of\ firm\ c\ at\ year\ t\}$$

$$E = \{e_{ij} | if\ similarity(v_i, v_j) \geq threshold\ e_{ij} = 1\ otherwise\ e_{ij} = 0\}$$

The Patent network ($G_{c,t}$) of firm c at time t is built as an unweighted and undirected network, where V and E represent sets of nodes and edges, respectively. V is a node constructing a firm's patent network, that is, patents granted to the firm until time t. Each patent is a vector represented by 0 and 1 according to its subgroup-level IPC code (e.g., H01L 21/285).

The similarity between patents can be measured by expressing them as vectors. In this study, the similarity is interpreted as the technological similarity between patents, measuring how similar the sublevel IPC code composition held by each patent is. We used the Jaccuard similarity, which is commonly used to measure the similarity of the components of two sets, as a metric (Besta et al., 2020). As of 2022, if each firm's patents have a similarity above the average Jaccuard similarity, the two patents are considered as related, and a link is formed.

As an example of the patent network, SunPower's patent network over time is presented in **Figure 6-5**. A firm's patent network expands and evolves with newly granted patents added every year. At this time, it is observed that most newly added patents follow the "preferential attachment" or "rich get richer" rule (Csárdi et al., 2007; Jeong et al., 2003; Newman, 2001). That is, the new patent forms a link with the central patent, in which the connections between the existing patents are mainly concentrated. Firms that strongly follow a preferential attachment to the evolution of patent networks gradually innovate based on existing technologies, which means that they have a strong exploitation routine for "Knowing." Therefore, the explorative or exploitative nature of the routine for *Knowing* can be identified by quantitatively measuring the degree of compliance with preferential attachment rules.

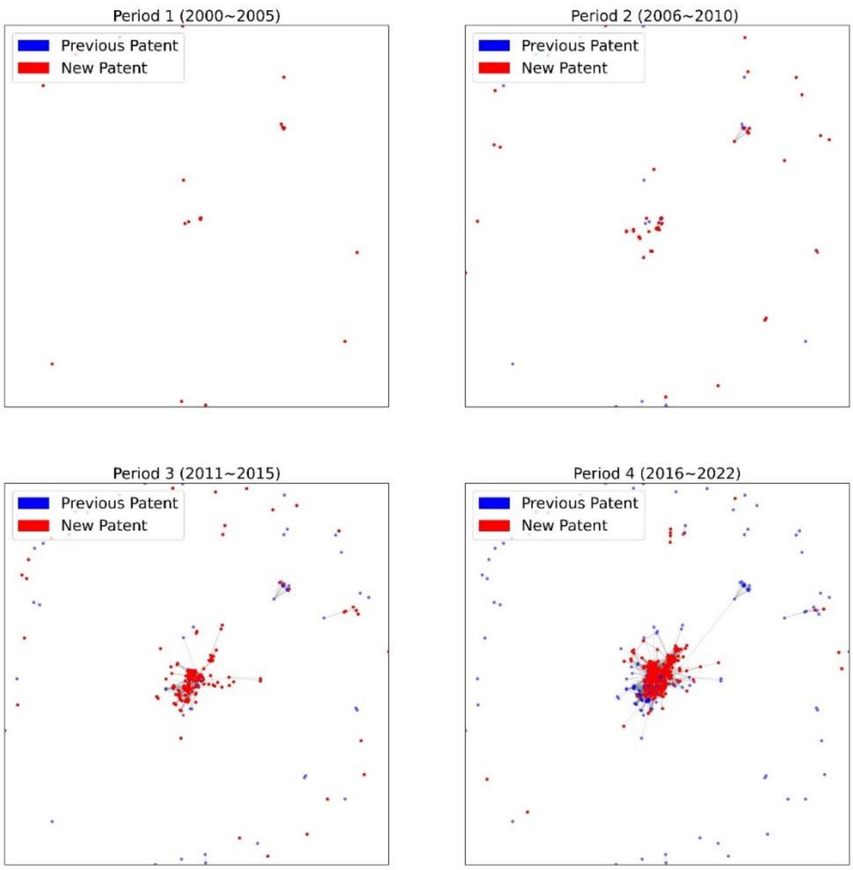


Figure 6-5. Patent network evolution of SunPower

The degree of preferential attachment in an evolving network can be measured using the attachment rate. $G_{c,t-1}$ and $G_{c,t}$ are the patent networks of firm c at time t-1 and t, respectively. Among the nodes of $G_{c,t-1}$, the probability ($P(v_k)$) that a node (v') appears newly at time t is connected to v_{k}, a node with a degree centrality value of k, as expressed in **Equation (6-3)**.

$$P(v_k) \propto A_k \qquad \text{Eq. (6-3)}$$

$$A_k = k^{\alpha} \qquad \text{Eq. (6-4)}$$

$\boldsymbol{A_k}$ is an attachment kernel. In case of the log-linear model, it is expressed as **Equation (6-4)**. In the Equation, the alpha value (α) is an attachment exponent. It is a linear preferential attachment (Scale Free Network) when $\alpha = 1$, a sub-linear preferential attachment when $0 < \alpha < 1$, a super-linear preferential attachment when $\alpha > 1$, and a random network when $\alpha = 0$. That is, the larger the value of α, the stronger the preferential attachment property. The general formula for the attachment kernel is **Equation (6-5)** (Jeong et al., 2003).

$$A_k(t) = \frac{m_k(t)N(t)}{n_k(t)m(t)} \qquad \text{Eq. (6-5)}$$

$A_k(t)$ in **Equation (6-5)** indicates the attachment rate of a node with a degree centrality k when the network $G_{c,t-1}$ evolves into $G_{c,t}$. $n_k(t)$ in the denominator indicates the number of nodes v_{k} with a degree centrality value of k in $G_{c,t-1}$, and $m(t)$ is the number of all newly formed links. $m_k(t)$ of the numerator is the number of links connected to v_{k} among the newly formed links at time t, and $N(t)$ is the number of existing nodes possessed by $G_{c,t-1}$ (Jeong et al., 2003).

There are various formulas for the attachment kernel; however, this study used the corrected Newman method to measure the attachment rate (Pham et al., 2015).

Eq. (6-6)

$$A_k = \frac{1}{\sum_t w_k(t)} \sum_{t=1}^{T} w_k(t) A_k(t)$$

$$w_k(t) = m(t) 1_{n_k(t) \neq 0}$$

The attachment rate expressed in **Equation (6-5)** may have an error value due to the length of time the network evolves. As a complement, the corrected Newman method is presented in **Equation (6-6)** (Newman, 2001; Pham et al., 2015). This method measures the attachment rate at every moment the network evolves, assigns more weight to the time when many links are created, and averages the weight.

In this study, the α value of k^{α} is estimated using the attachment rate measured by the corrected Newman method (Kunegis et al., 2013). For estimation, the log was taken on both sides of **Equation (6-4)**, and the ordinary least squares method was used. By defining the value of α as the firm's willingness for novelty, it is possible to quantitatively grasp how much the firm follows the rule of preferential attachment in *Knowing* for technology development. A firm with a larger α has an exploitative routine for *Knowing* and innovates based on existing knowledge and technology. On the other hand, a firm with a large $1-\alpha$ has an explorative routine for *Knowing* and innovates through new knowledge and technology.

6.3.2.2 Measuring Routine for *Doing* behavior

In this section, the firm's innovation routine for *Doing* is quantitatively measured using photovoltaic module data. Unlike patents, which are continuously filed and granted each year, firms do not release their products every year. In general, firms conduct sales activities with products of the corresponding design after the product launch and launch new products when market competitiveness changes (Golder & Tellis, 2004; He et al., 2019; Rink & Swan, 1979; Shahmarichatghieh et al., 2015). Due to these differences, patent and product data have different characteristics and require suitable analysis methods. Therefore, we adopt a different approach from Section 6.2.3, in order to measure a firm's routine using product data. Specifically, we measured the characteristic probability distribution of each firm's products and observed its changes over time. The degree of this change is defined as the firm's willingness for novelty for *Doing*, and either the explorative or exploitative nature of the routine is derived.

A firm's products consist of detailed technological characteristics (Saviotti, 1985;

Saviotti & Metcalfe, 1984). For example, tanks comprise armor thickness, speed, and weight (Castaldi et al., 2009), whereas mobile products comprise CPU speed and image quality (J.-D. Lee et al., 2022). This study considered three technological characteristics of photovoltaic products: photovoltaic cell technology, module efficiency, and nominal power. Then, the probability mass function (PMF) for the three characteristics of the products produced up to a certain time T is derived using **Equation (6-7)**.

$$PMF_T(X = x) = \frac{\sum_{t \le T} Product_{i,t,x}}{\sum_{t \le T} Product_{i,t}} \qquad \text{Eq. (6-7)}$$

Equation (6-7) is a probability mass function when X technology characteristic at period T is x value. $\sum_{t \le T} \boldsymbol{Product_{i,t,x}}$ is the number of products whose X technological characteristic has x value among the products released by time T, and $\sum_{t \le T} \boldsymbol{Product_{i,t}}$ is the total number of products released up to time T.

Figure 6-6 shows the results of plotting the change in the probability distribution of each of the three technological characteristics released during the periods of (1) 2000 to 2010 (red), and (2) 2000 to 2022 (blue). The probability distributions of the efficiency and nominal power shifted to the right, and a more uniform distribution was observed. In other words, the level of technological characteristics increased over time, and products with various efficiencies and nominal powers were released. However, in the case of photovoltaic cell technology applied to modules, both mono-crystalline and multi-crystalline silicon photovoltaic cell technologies have become far more dominant than before. This suggests that the crystalline silicon photovoltaic cell module has become the dominant design in terms of photovoltaic technology.

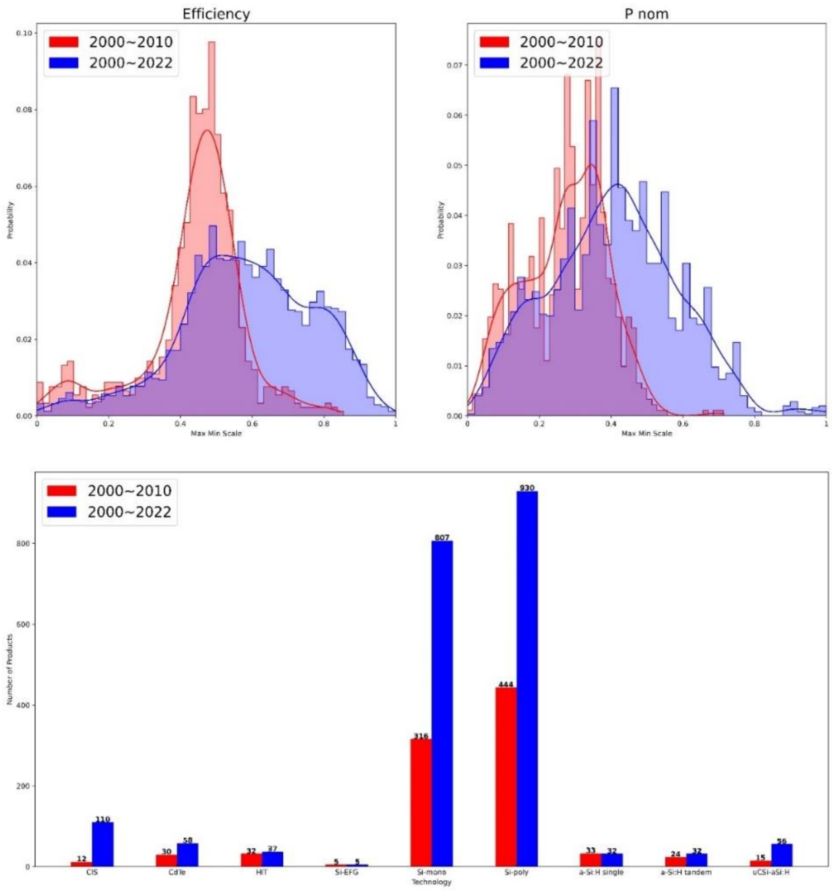


Figure 6-6. Probability Mass Function of technological characteristics for all products

Equation (6-7) is applied to the product data of each firm to derive the probability distribution of the technological characteristics of the products released by each firm every year. The firm's willingness for novelty for *Doing* is derived by measuring the distance between the probability distribution functions of the technological characteristics of the firms conducted in this way.

$$KLD\left(PMF_{c,T}(X), M\right) = \sum_{x \in X} PMF_{c,T}(x) \log\left(\frac{PMF_{c,T}(x)}{M(x)}\right) \qquad \text{Eq. (6-8)}$$

$$M = \frac{1}{2}\left(PMF_{c,T} + PMF_{c,T'}\right)$$

$$JSD\left(PMF_{c,T}, PMF_{c,T'}\right) = \frac{1}{2}KLD\left(PMF_{c,T}, M\right) + \frac{1}{2}KLD\left(PMF_{c,T'}, M\right)$$

The Jensen-Shannon Divergence (JSD) is used as a metric to measure the distance between probability distributions (**Equation (6-2)**). The JSD is a measure that derives the distance between distributions, and is proposed as a measure of distance by compensating for the asymmetry of the Kullback-Leibler Divergence (KLD) (Kullback & Leibler, 1951; Shannon, 1948; Wu et al. al., 2021)[43]. $\boldsymbol{PMF_{c,T}(X)}$ is the probability mass function of the characteristic X of the technology at time T of firm c, and $\boldsymbol{PMF_{c,T'}(X)}$ is that of time $\boldsymbol{T'}$. M is the mid-distribution between the two probability distributions. Changes in the probability distribution of the three characteristics between the first time and last time a

[43] KLD is a function that computes the difference between distributions using the concept of information gain. The definition of KLD between different distributions P(x), Q(x) for the same random variable x is as follows: $D_{KL}(P|Q) = E_{X\sim P}[\log\frac{P(X)}{Q(X)}] = \sum_x(P(x)\log\frac{P(x)}{Q(x)}) = \sum_x(P(x)\log P(x) - P(x)\log Q(x))$.
When the probability distributions P(x) and Q(x) are identical, $D_{KL}(P|Q)$=0, and vice versa. In addition, the value of $D_{KL}(\cdot)$ is always greater than zero. However, since KLD is asymmetry, it can represent the difference between two distributions, but not the distance.

product was released were measured using the JSD, and the sum of these changes was defined as the willingness for novelty.

6.3.3 Relative Classification of Routines within a Sectoral Regime

Table 6-3 summarizes the discussion thus far on quantifying innovation routines in a firm's *Knowing* (Section 6.2.3) and *Doing* (Section 6.2.4).

Table 6-3. Innovation routines by *Knowing* and *Doing*

	Knowing		Doing	
	Explorative	**Exploitative**	**Explorative**	**Exploitative**
Method	α = Attachment exponent Level of Preferential Attachment		$\sum_{X_i} JSD(PMF_{c,T} PMF_{c,T_0}))$ = Distance between probability distribution of product′s technical characterisitcs year T and T_0	
Measure	$0 < \alpha$		$\sum_{X_i} JSD(PMF_{c,T} PMF_{c,T_0})) \geq 0$	
	0	**(+)**	**(+)**	**0**

We derive the innovation routine for *Knowing* by measuring the extent to which a firm's patent network follows a preferential attachment rule. The larger the value of α, which indicates the degree of preferential attachment of each firm's patent network, the more exploitative the firm is, and conversely, the smaller the value of α, the more explorative it is. On the other hand, the innovation routine for *Doing* is derived by measuring how differentiated technological characteristics in a new product are compared to previously released products through JSD. The higher the JSD value, the greater the difference between the newly released product and the existing product. Therefore, firms follow an explorative routine.

As explained in the section 6.1, a comparison of routines between firms must be relative within the same sectoral regime. In this study, the influence of the sectoral regime is controlled because the analysis target is limited to firms that manufacture core value chains in the photovoltaic industry. However, it is necessary to control for the influence of external environmental changes over time. Firm behavior is the result of the interaction between a unique routine and a given environment, and different behaviors can be derived from the same routine in the environmental context in which a firm is located each year. For example, if a firm has an explorative innovation routine, but reduced R&D activities during a global recession, its innovation behavior in that year can be observed to be more exploitative than before. The dynamics of the external environment are a selection pressure that all firms in the same industry are affected by. Therefore, the changes in the average are representative of the external influences that existed across the industry at that time.

This study attempted to correct the influence of environmental factors by max-min scaling the values of α and JSD for each firm each year and subtracting the average value for that year. Using these adjusted values of α and JSD, each firm's innovation routine was expressed for every year during the analysis period. Consequently, each firm has a quantified innovation routine value for *Knowing* and *Doing* every year.

In addition, as **Equation (6-1)** suggests, a firm's innovation routine is expressed as an ordered pair of each innovation routine for *Knowing* and *Doing.* The coordinate value of the innovation routine in *Knowing* is expressed by subtracting the adjusted α value from 1. The coordinate values of the routine in *Doing* are expressed as adjusted JSD values. Thus, we derived the firm's innovation routine coordinates for each year (**Equation (6-9)**).

$$\begin{aligned} &\boldsymbol{x_c^{Innovation}(t)} \\ &= (\boldsymbol{x_c^{Exploration}(t)}, \boldsymbol{x_c^{Exploitation}(t)}) \\ &= \left(\boldsymbol{1 - \alpha_c^{adjust}(t)}, \sum\nolimits_{X_i} \boldsymbol{JSD^{adjust}(PMF_{c,t} PMF_{c,T_0})}) \right) \end{aligned} \quad \text{Eq. (6-9)}$$

6.3.4 Regression Analysis

In this section, the types of innovation routine for the taxa in the evolutionary phylogenetic tree of photovoltaic technology (**Chapter 4**) are established and used to examine the relation between diversity dynamics and innovation routine types and, and further, technological search. First, the type of routine for each taxon is derived as shown in **Equation (6-10).**

$$\begin{aligned} &Routine\ Dummy\ of\ Taxon_{jt} = 1 \\ &\text{if } Patent\left(Taxon_{jt}\right) \cap Patent(Routine\ Firm's\ Patent) \neq \emptyset \\ &otherwise, Routine\ Dummy\ of\ Taxon_{jt} = 0 \end{aligned} \quad \text{Eq. (6-10)}$$

The routine type of a $Taxon_{jt}$ in the photovoltaic technology evolutionary tree follows the patents within $Taxon_{jt}$ and the type of firm as its assignee. They are represented by dummy variables that are 1 if they are included in a particular routine type, and 0 otherwise. In addition, just as in biology there are many different genes within a given species, a certain technological taxon can be expressed by more than one routine.

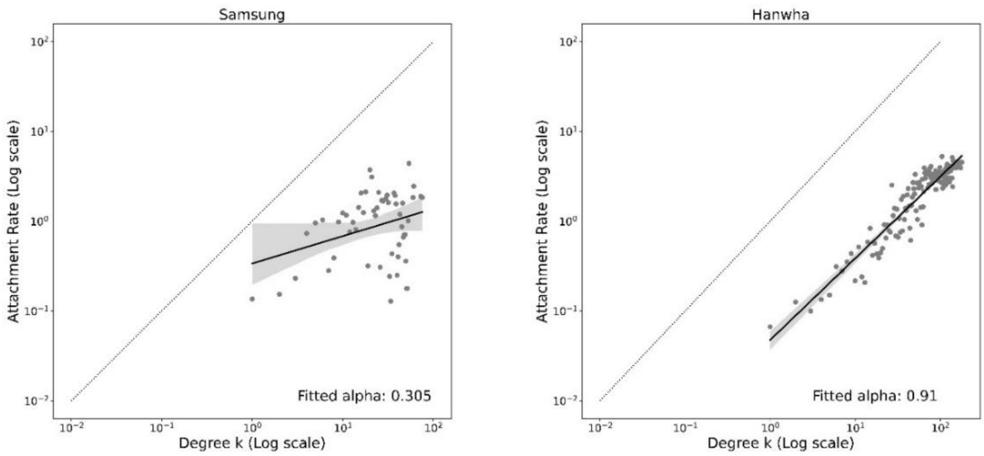
$$\begin{aligned} TD_{jt} = \beta_0 + \beta_1 VI_{jt} + \beta_2 HGT_{jt} + \beta_3 MT_{jt} + \gamma_0^t \\ + \sum_k \beta_k \, Control\ Variables_k \\ + \sum_m \beta_m Routine\ Dummy_{jtm} \\ + \beta_r^{VI} Routine\ Dummy_{jtr} VI_{jt} \\ + \beta_r^{HGT} Routine\ Dummy_{jtr} HGT_{jt} \\ + \beta_r^{MT} Routine\ Dummy_{jtr} MT_{jt} + \varepsilon_{jt} \end{aligned} \qquad \text{Eq. (6-11)}$$

The routine dummy variables for each taxon are then introduced as additional variables into the existing regression equations (**Equations (5-6)**) to analyze the dynamics of technological diversity and the patterns of search, resulting in the regression equations, **Equations (6-10)**. An independent routine dummy term ($\sum_m \beta_m Routine\ Dummy_{jtm}$) is added to show the independent effect of taxa's routine type, and an interaction term of search and routine dummy is added to describe the interaction with technological search ($\beta_r^{VI}, \beta_r^{HGT}, \beta_r^{MT}$).

6.4 Organizational Routine as a Micro Criteria to Diversity Dynamics

6.4.1 Innovation Routines of Photovoltaic Firms

In this section, the analysis of identifying innovation routines of photovoltaic firms is presented. First, the results from *Knowing* and *Doing* are discussed, respectively. Then four types of innovation routines are observed through routine coordinate.



(a) Samsung **(b) Hanwha**

Figure 6-7. Attachment Rate (log scale) – Degree (log scale) scatter plot

Figure 6-7 shows the results of estimating the statistically significant α of Samsung and Hanwha with a log-scaled attachment rate and exponential centrality k on their patent networks, which evolved by 2022 (p-value < 0.05). Samsung's α value was 0.305. This means that Samsung's willingness for novelty for *Knowing* is exploitative by 0.305 and explorative by 0.695. In contrast, Hanwha's α value is 0.910. This means that Hanwha has a very strong exploitative routine in innovation for *Knowing* and generally utilizes existing knowledge and technology in a familiar space.

Table 6-4. Level of willingness for novelty of *Knowing* in 19 firms ($p < 0.05$)

Rank	**Firm**	**willingness for novelty (1-α)**	**# of patents**	**Rank**	**Firm**	**willingness for novelty (1-α)**	**# of patents**
1	Samsung	0.695	150	11	Kaneka	0.171	183
2	TSMC Solar	0.667	183	12	Solar World	0.157	65
3	Sharp	0.566	132	13	SunPower	0.152	738
4	Schott Solar	0.561	91	14	Fuji Electric	0.139	853
5	Kyocera	0.538	270	15	First Solar	0.119	249
6	Panasonic	0.499	290	16	Hanwha	0.09	671
7	Bosch Solar Energy	0.483	359	17	BP Solar	-0.087	536
8	GE	0.462	555	-	Global Solar Energy	1.391	24
9	LG	0.4	534	-	REC	-0.001	19
10	Mitsubishi	0.291	83				

Table 6-4 shows the explorative degree of willingness for novelty (1- α) for *Knowing* and the number of patents owned by 19 firms. The firm with the most exploratory innovation routine in *Knowing* is Samsung, followed by TSMC Solar and Sharp[44]. These firms actively introduce new technologies outside the existing technology space. Excluding the top six firms, the explorative degree of thirteen firms was less than 0.5. This suggests that the firms in this study primarily innovated based on existing technologies in the photovoltaic industry. On the other hand, the firm with the most exploitative innovation routines was BP Solar. The α values of BP Solar and REC exceed 1, which means that they are only developing technology to deepen their own knowledge. Meanwhile, the number of patents and explorative innovation routines are irrelevant. Regardless of whether the number of granted patents is large or small, even if firms have the same number of patents, a firm's technological development creates innovations of different attributes based on its unique search routine.

Table 6-5 presents the results of the explorative degree of the innovation routine in *Doing* and the number of products for each firm. Each figure is the sum of the differences in the probability distribution of the three technological characteristics between the first and last product launches by 2022. The higher the number, the greater the differentiation of the new product compared to the existing product, which means that it has an explorative innovation routine for *Doing*. Among the 19 photovoltaic firms, firms from 1st to 10th, such as Solar World, Bosch Solar Energy, and Hanwha, showed a willingness for novelty

[44] The highest value is shown in Global Solar Energy, however, due to the lack of observations, relative comparison is not reasonable.

of 1.0 or more, indicating a relatively more explorative innovation routine. However, values below 0.5 were derived for Global Solar Energy, Samsung, and Fuji Electric, indicating that they mainly launched new products with little introduction of new technologies.

Table 6-5. Level of willingness for novelty of *Doing* in 19 firms

Rank	Firm	willingness for novelty ($\sum_{X_i} JSD(PMF_{c,2018}P$	# of products	Rank	Firm	willingness for novelty ($\sum_{X_i} JSD(PMF_{c,2018}PMI$	# of products
1	Solar World	1.545	79	11	Panasonic	0.957	37
2	Schott Solar	1.465	95	12	Kyocera	0.882	32
3	Bosch Solar Energy	1.461	46	13	Mitsubishi	0.855	38
4	Hanwha	1.329	293	14	BP Solar	0.670	35
5	REC	1.264	95	15	TSMC Solar	0.637	9
6	First Solar	1.241	61	16	GE	0.554	10
7	LG	1.236	70	17	Global Solar Energy	0.449	15
8	SunPower	1.127	59	18	Samsung	0.235	11
9	Kaneka	1.085	17	19	Fuji Electric	0.191	4
10	Sharp	1.053	113				

The results in Tables 6-4 and 6-5 do not reflect the impact of the external environment that existed at each point in time. Especially, in the case of Table 6-5, comparisons across firms are unreasonable given the distinct product release dates for each firm. Therefore, a correction for time-specific external impacts is needed, as discussed in Section 6.3.3.

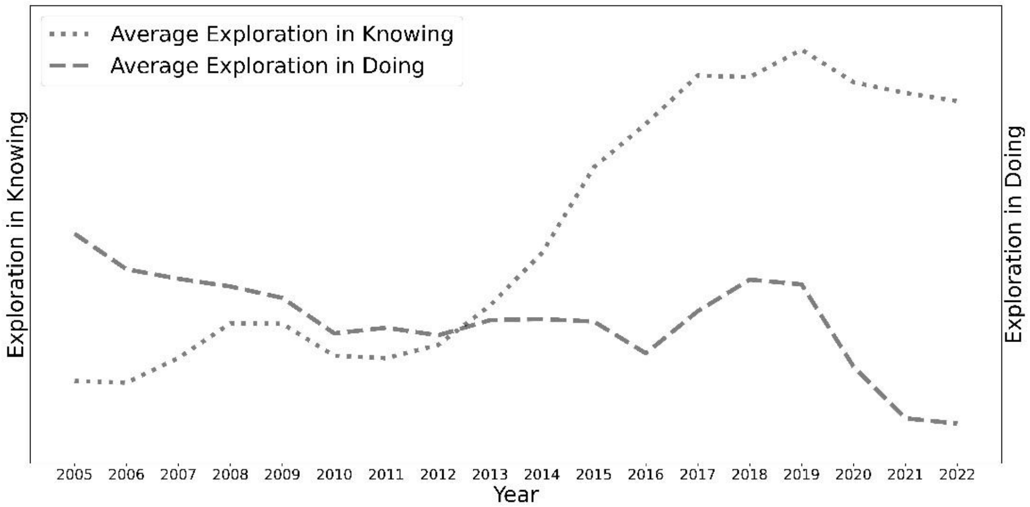


Figure 6-8. Average routine changes: Level of exploration for *Knowing* and *Doing*

Figure 6-8 shows the average routine changes for the 19 firms analyzed in the previous section. In this study, since the number of firms analyzed was limited to 19, it is unreasonable to assume that their average tendencies represent the dynamics of the industry. Nevertheless, it was confirmed that industrial issues and trends coincide, as discussed in Chapter 3. More specifically, during the downturn of the photovoltaic industry, as in *Period 3* in **Table 3-1**, a decrease in explorative routines in both *Knowing* and *Doing* is confirmed. Particularly for “Knowing,” all periods except for the downturn show a positive slope. The change in dominant design due to the increase in the speed and scope of innovation in the photovoltaic industry may have triggered a change in the trend from 2015 to 2019 in "Doing," which previously showed a steady decline.

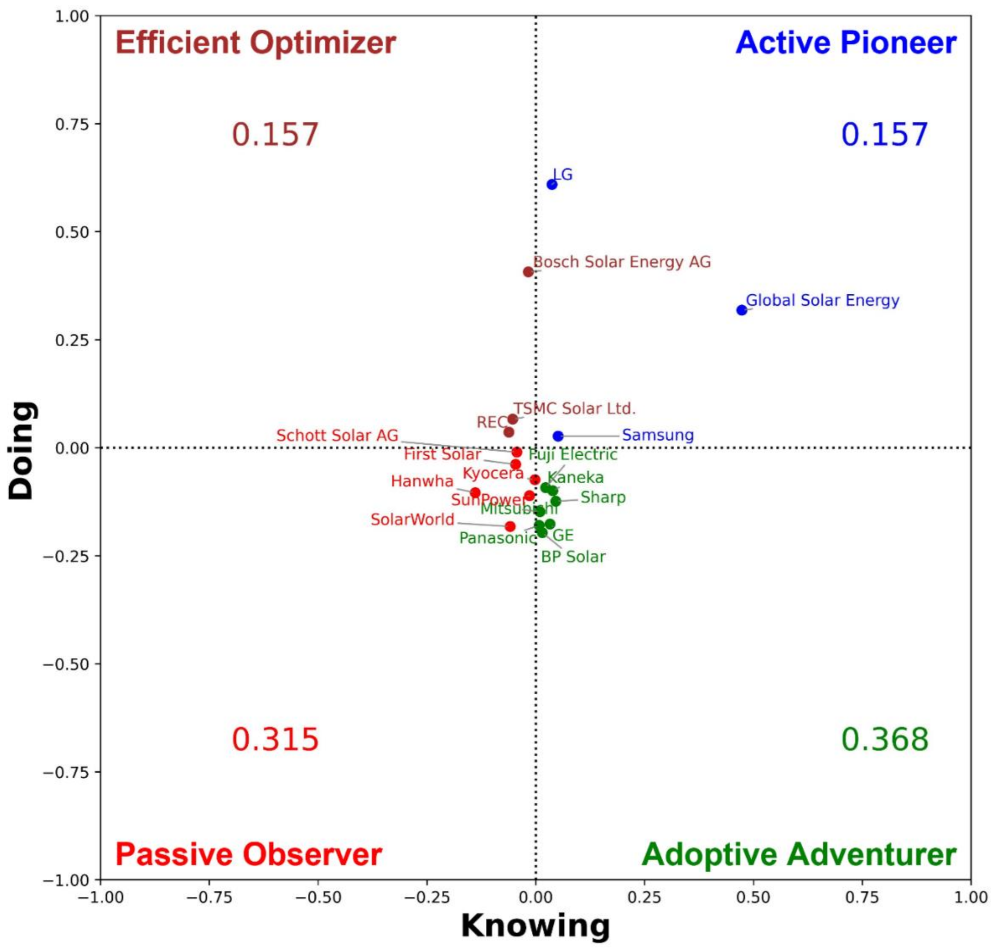


Figure 6-9. Innovation routines of each photovoltaic firm

Figure 6-9 represents the average innovation routine coordinates of each of the 19 firms. Each point in the figure represents the coordinates of a given firm's average innovation routine. Among the 19 firms, the active pioneer type (quadrant 1) and the efficient optimizer type (quadrant 2) each contain three firms, accounting for 15.7% of the total. The passive observer type in the third quadrant has six firms (31.5%), while the adaptive explorer type had seven firms (36.8%) in the fourth quadrant. Nineteen firms had innovation routines that were more heterogeneous in *Knowing* than in *Doing*. The explorative and exploitative for *Knowing* are similarly divided into 52.8% and 47.2%, respectively. However, the explorative and exploitative for *Doing* are 31.4% and 68.6%, respectively, showing a difference of approximately two times. In other words, the photovoltaic firms used in the analysis have a homogeneous tendency toward exploitative innovation routines for *Doing*.

Table 6-6. Type of innovation routines for each photovoltaic firm

Efficient Optimizer (Quadrant 2)	Active Pioneer (Quadrant 1)
Bosch Solar Energy	Global Solar Energy
REC	LG
Schott Solar AG	Samsung
TSMC Solar	
Passive Observer (Quadrant 3)	**Adoptive Adventurer (Quadrant 4)**
First Solar	BP Solar
Hanwha	Fuji Electric
Kyocera	GE
Solar World	Kaneka
SunPower	Mitsubishi
	Panasonic
	Sharp

The type of innovation routines for each of 19 firms are shown in **Table 6-6**. It is important to note that the innovation routines derived from this study are a measure of a firm's propensity to be novel, not of the innovativeness of its technology. For example, SunPower is considered to have high technological competency for implementing the innovation of inter-digitized back-contact technology, but it is identified a passive observer type in the innovation routines.

The innovation routine derived from this study is consistent with the results of the previous studies in Chapter 2, which argued that routine is a firm-specific characteristic (see **Figures 6-10, 6-11**).

First, through the dense phenomenon observed in each firm's annual routine in Figure 11, we found that each firm's innovation routine was maintained or gradually changed over a long period. Firms such as GE and Sharp maintained their existing innovation types by repeating the innovation routine, even though there were environmental changes in the photovoltaic industry during the analysis period, as shown in Table 6. Recurrence is a key characteristic of routines (Becker, 2004; Cohen et al., 1996). Repeated routines have path dependencies based on experience and become unique characteristics that are difficult for other firms to imitate (Day, 1994; Dierickx & Cool, 1989; Nelson & Winter, 1982). However, the recurrence of a routine based on the past reflects its processual nature (Becker, 2004). Firms gradually adapt to a given environment based on feedback on outcomes, and endogenous changes occur during this process (Becker et al., 2006; Nelson & Winter, 1982; Winter & Szulanski, 2000).

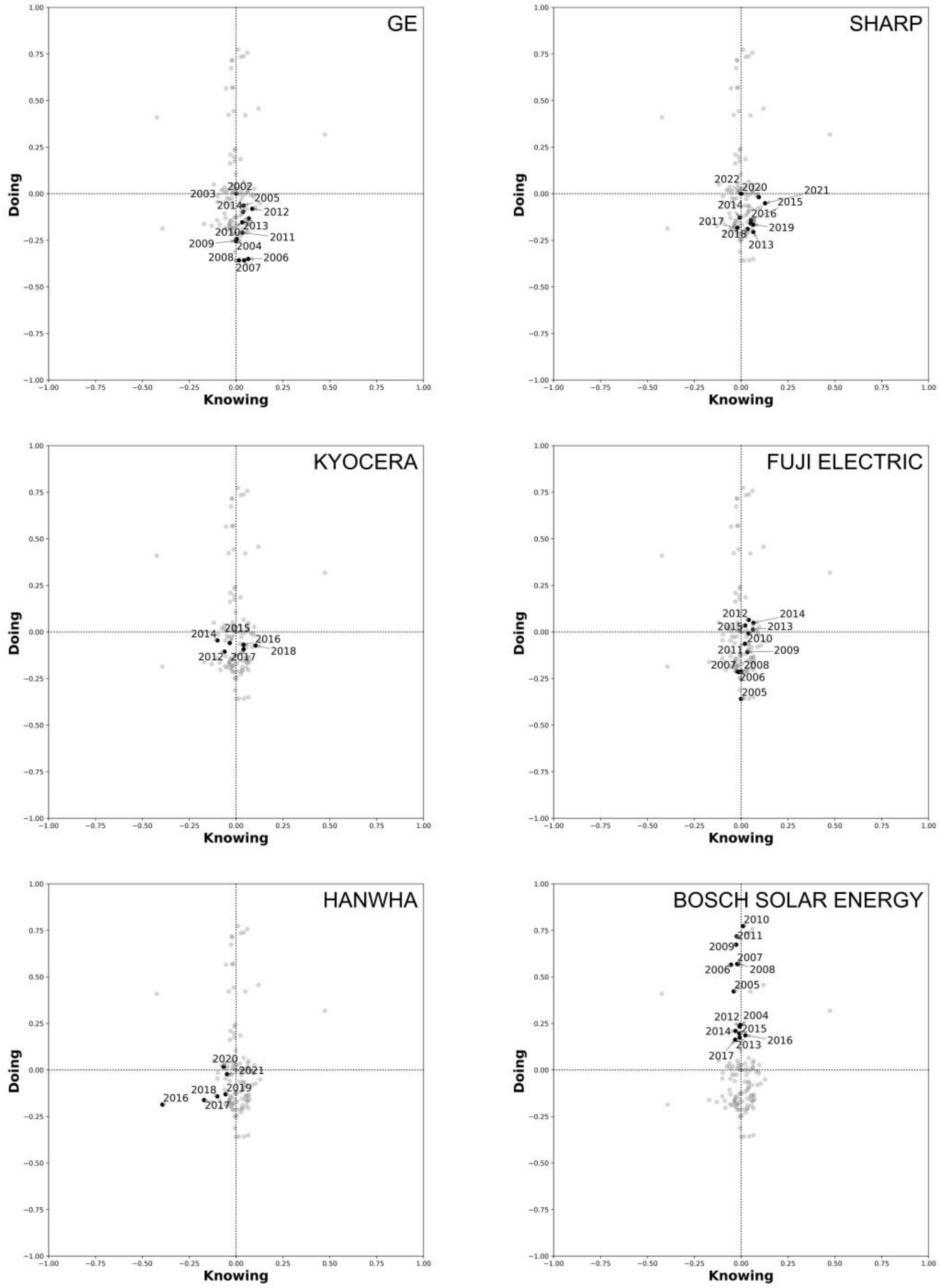


Figure 6-10. Annual innovation routine of each selected firm

To discuss **Figure 6-10** in more detail, a gradual change in routines was observed for Kyocera, Fuji Electric, Hanwha, and Bosch Solar Energy. First, Kyocera, Fuji Electric, and Hanwha were observed to have changed their innovation types through willingness for novelty that increased gradually each year. Kyocera increased their willingness for novelty in *Knowing*, and Fuji Electric in *Doing*. In the case of Hanwha, the willingness for novelty increased in both *Knowing* and *Doing*. Gradual change is an essential characteristic of routines. A series of steady changes over time leads to more substantive changes and adaptation to new circumstances (Becker, 2004).

Bosch Solar Energy, on the other hand, displays a more drastic routine change within the innovation type. Bosch Solar Energy steadily increased the willingness for novelty of *Doing* since 2004, when data were observed with the Efficient Optimizer type. However, this trend reversed from 2010, with a large decrease between 2011 and 2012. Since then, Bosh Solar Energy has maintained a changed or reduced innovation routine. Bosh Solar Energy established a new plant in 2010 and subsequently made significant investments in the photovoltaic business by acquiring a US solar module manufacturer but announced its exit in 2013. Chapter 2 explained that radical change was avoided from the viewpoint of evolution and revealed that routine changes gradually and progressively. Further research is required to identify the causal relationship; however, Bosh Solar Energy suggests that there is a relationship between the life and death of firms and radical changes in routines.

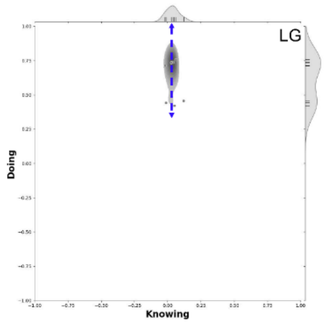
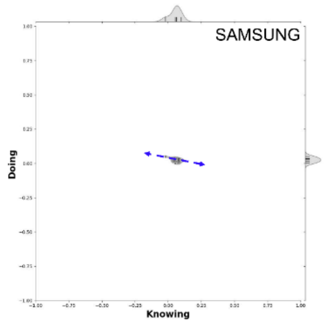
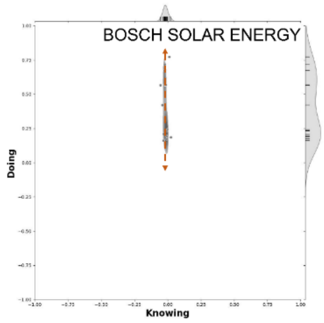
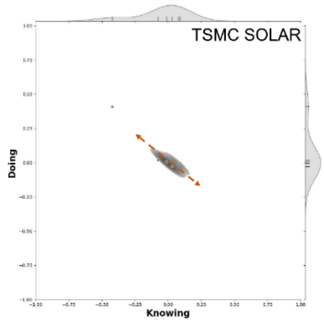
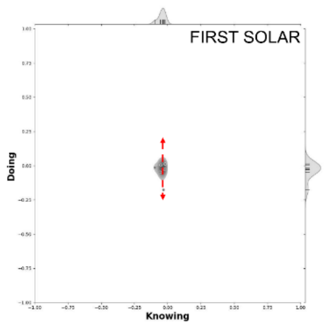
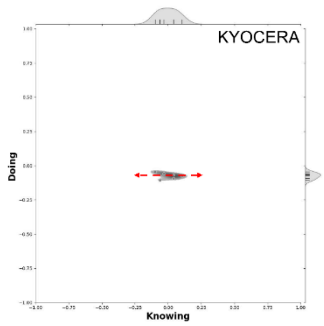
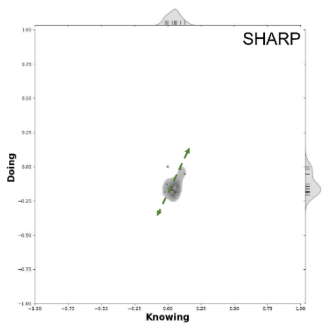
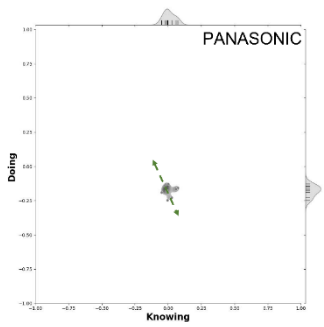
Active Pioneer (Quadrant 1)		
Efficient Optimizer (Quadrant 2)		
Passive Observer (Quadrant 3)		
Adoptive Adventurer (Quadrant 4)		

Figure 6-11. Routine contour of each firm by type

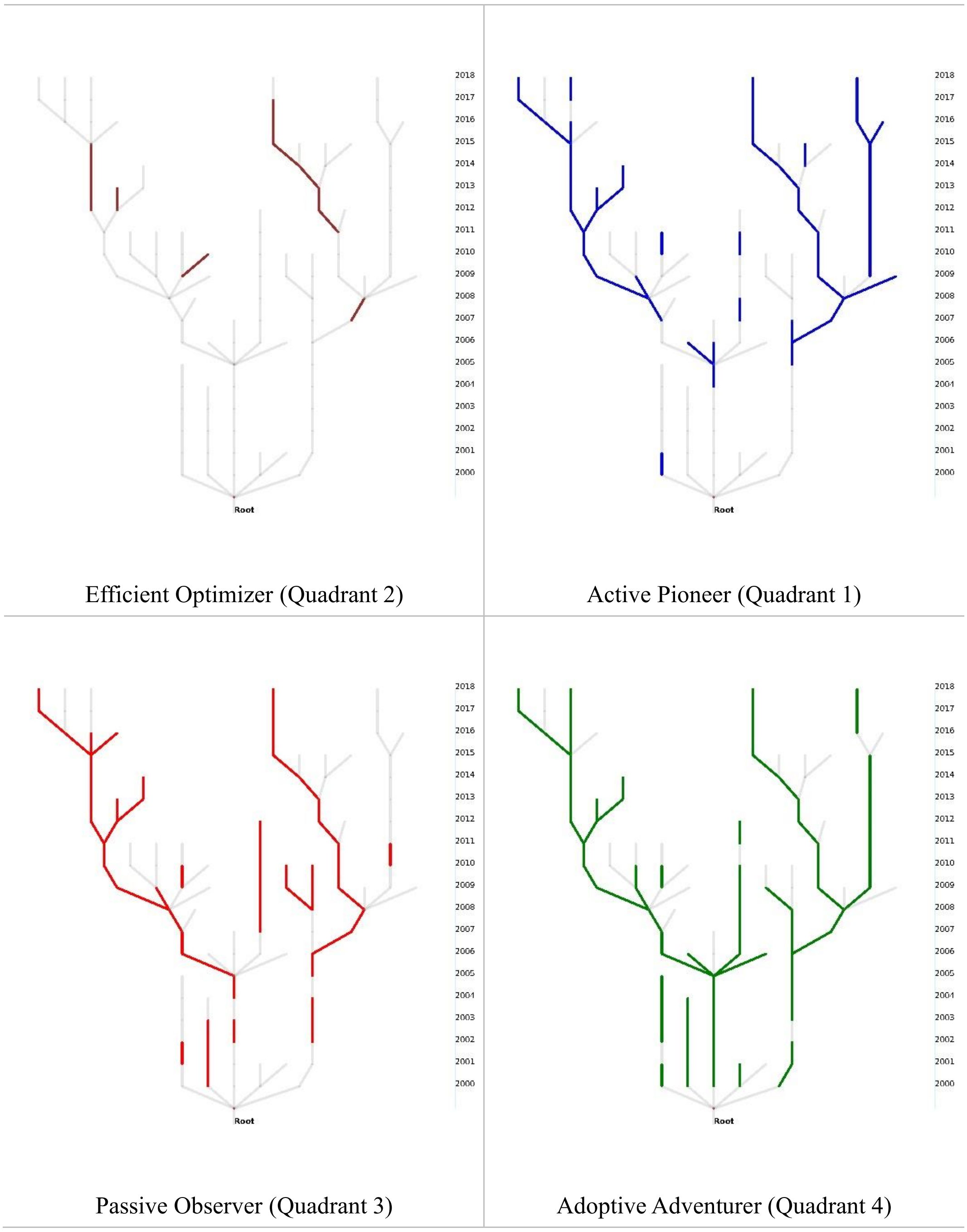
Figure 6-11 shows that even within the same innovation type, each firm has a unique innovation routine. As a concrete example, First Solar and Kyocera's average innovation routines fall under the Passive Observer category. However, in terms of their innovation type, First Solar shows a vertical aspect, whereas Kyocera shows a horizontal aspect. In other words, both firms have exploitative innovation routines in *Knowing* and *Doing*, but their directions are vertically and horizontally different. When the environment changes, First Solar will respond with a differentiated *Doing* routine, and Kyocera with a *Knowing* routine. Therefore, after a long period of time, there is a possibility that the two firms will become very heterogeneous or, isomorphic, through changes in their innovation routines.

In summary, the firm's innovation routine identifies willingness for novelty values in which the influence of the external environment is controlled for in *Knowing* and *Doing*. It was observed that 68.6% of the 19 firms in the photovoltaic industry showed an exploitative innovation routine for *Doing*, thus performing more stably and resembling innovations in production compared to technology development. In *Knowing*, the adaptive explorer type with an explorative innovation routine accounted for the largest portion (36.8 %). We find that firms' innovation routines do not change significantly over time and undergo gradual changes. This means that firms continue to act within a specific category, proving the basic theory of evolutionary economics in which firms make routine-based satisfying choices with bounded rationality (Foss, 2003; Nelson & Winter, 1982; Simon, 1990; Simon, 1997). Furthermore, within each type, it was observed that each firm had a unique innovation routine aspect. Therefore, the innovation routines of the firms derived from the results are different and have unique characteristics, suggesting that the routine identification method presented in this study is effective.

6.4.2 Relation between Diversity Dynamics and Organizational Routines

This section establishes the relationship between technological diversity and organizational routines. The technological diversity derived in Chapter 4 covers the overall technologies produced across the photovoltaic sector, from wide range of agents such as universities, research institutes, and companies. Therefore, we analyze the impact of organizational routines on the technological evolution of the entire sector.

To begin, the types of innovation routines are represented for each taxon in evolutionary phylogenetic tree of photovoltaic technology, resulted previously in Figure 4-2. The result is shown in **Figure 6-12**. The figure shows that the characteristics of each type presented in Section 6.2.3 are reflected in the aspects of technological evolution, and that the evolutionary patterns depend on each type of innovation routine. More specifically, AP and AA types, both explorative in *Knowing*, are represented in all major technological trajectories, such as root to [2018_1], [2018_2], and [2018_3]. The speciation of the lineage also all oriented from these two types. Conversely, EO and PO types, both exploitative in *Knowing*, are observed in the lineages of [2018_1] and [2018_2]. This means, these two types developed the first- and second-generation technologies for which a market exists.



Efficient Optimizer (Quadrant 2) | Active Pioneer (Quadrant 1)

Passive Observer (Quadrant 3) | Adoptive Adventurer (Quadrant 4)

Figure 6-12. Type of innovation routines on evolutionary phylogenetic tree

Calculating the number of patents per firm as a simple average of the total patents for each type[45], AA types has the most with 376 patents per firm while EP types have the least with 187. Despite the difference in in the number of patents held, however, EO types are hardly identified on the evolutionary phylogenetic tree compared to the other types. EO types are highly exploitative in *Doing*, so they prioritize product development through process innovation than patentable R&D. The phenomenon observed in the evolutionary phylogenetic tree of technology can be seen as the reflection of characteristic on type. Moreover, AP types are mostly observed after the mid-2000s, because two of the three companies in this type, LG and Samsung, started their photovoltaic businesses by then.

The patterns of technological evolution by each type of innovation routines examined in the evolutionary phylogenetic tree suggest that organizational routines are related to technological evolution. To confirm the relationship quantitatively and specifically, this study conducted a regression analysis for technological diversity and organizational routines.

[45] The number of patents per company for the other types is 236 for AP types and 347 for PO Types. The total number of patents by type is 708 for AP types, 561 for EO types, 2,084 for PO types, and 2,632 for AA types.

Table 6-7. Result of regression

Dependent variable: Entropy	Model 1
Intercept	**-0.292*** **(0.147)**
Vertical Inheritance (VI) of Taxon	**-0.265***** **(0.079)**
Horizontal Gene Transfer (HGT) of Taxon	**0.268***** **(0.059)**
Mutation (MT) of Taxon	-0.028 (0.061)
Gene Pool Size	**0.350***** **(0.083)**
Global Gene Pool Size	**0.374***** **(0.083)**
Number of patents in Taxon	**0.440***** **(0.124)**
Active Pioneer (AP) Dummy	0.166 (0.134)
Efficient Optimizer (EO) Dummy	-0.178 (0.232)
Passive Observer (PO) Dummy	-0.142 (0.123)
Adoptive Adventure (AA) Dummy	**0.405**** **(0.144)**
Number of Obs.	103
Likelihood	-92.551

Notes:

1. Standard errors are in parentheses.

2. ***, **, and *denote statistical significance at the 0.1%, 1%, and 5%levels, respectively.

3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Table 6-7 shows the results of the regression analysis. **Model 1** analyzes the dynamics of diversity, considering both the technological search derived in Chapter 5 and the types of innovation routines in this chapter as explanatory variables. Consistent with the findings in the previous chapter, technological diversity is statistically significant but either negatively (-) or positively (+) related to VI or HGT, respectively. the results of the control variables also show a significantly positive relationship between technological diversity and the genetic pool whether direct or neighboring ancestors.

In terms of the relationship between innovation routine type and technology diversity, only the AA type is statistically significant. The relationship is positive, indicating that the AA types influence the increase in technological diversity in the sector.

To further explore the specific relationship of diversity mechanisms to innovation routines, additional regression analysis is conducted for interactive variables between the four innovation types and the three exploration patterns. However, only significant results are presented and discussed in this section (**Models 2-5** in **Table 6-8**). For other results not presented in this section, please refer to the appendix.

Table 6-8. Result of regression for interactive variables

Dependent variable: Entropy	Model 2 AA * HGT	Model 3 AP * MT	Model 4 EP * MT	Model 5 PO * HGT
Intercept	-0.255 (0.127)	-0.065 (0.100)	0.021 (0.087)	0.195 (0.126)
Search of Taxon	0.072 (0.075)	0.025 (0.056)	0.060 (0.063)	**0.788** (0.304)**
Active Pioneer (AP) Dummy		**0.336** (0.128)**		
Active Pioneer * Search of Taxon		**1.674*** (0.316)**		
Efficient Optimizer (EO) Dummy			0.222 (0.272)	
Efficient Optimizer * Search of Taxon			**2.725** (0.978)**	
Passive Observer (PO) Dummy				-0.245 (0.144)
Passive Observer * Search of Taxon				-0.591 (0.307)
Adoptive Adventurer (AA) Dummy	**0.346* (0.139)**			
Adoptive Adventurer * Search of Taxon	**0.303** (0.110)**			
Gene Pool Size	**0.454*** (0.080)**	**0.336*** (0.073)**	**0.349*** (0.082)**	**0.385*** (0.080)**
Global Gene Pool Size	**0.346*** (0.073)**	**0.382*** (0.078)**	**0.305*** (0.079)**	**0.325*** (0.077)**
Number of patents in Taxon	**0.202* (0.087)**	**0.335*** (0.078)**	**0.437*** (0.092)**	**0.347*** (0.084)**
Number of Obs.	103	103	103	103
Likelihood	-91.375	-87.466	-96.463	-94.837

Notes:
1. Standard errors are in parentheses.
2. ***, **, and *denote statistical significance at the 0.1%, 1%, and 5%levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5%levels.

The interaction between AA and HGT is analyzed in **Model 2**. The result shows significantly positive relationship between technological diversity and HGT performed by AA. In Chapter 5, we pointed out finding novel combinations of technologies using new technological elements from neighboring ancestors that can be identified in the technological evolutionary tree, that is HGT, is the principle of increasing technological diversity. The result of Model 2 suggests that HGT contributes to an increase in overall technological diversity, especially when it is performed by AA types. It emphasizes the importance of combinatorial innovation concluded in previous chapter, as well as implies that organizational routine making decisions of technological search affect the entire technological evolution of the sector.

The other three types, not statistically significant in Model 1, were also correlated with technological diversity through an interaction with technological search. First, **Models 3 and 4** show the regression results of interactions for MT with AP or EO. In Chapter 5, MT did not have a significant relation with diversity dynamics. Like HGT, MT combines external technologies rather than the deepening of existing technologies, but it introduces a completely new domain of technology, which increases the risk of adaptation from an evolutionary perspective (Kardong, 2005). However, MT interacted with AP or EO improves the technological diversity at a high significance level of 0.1%. The types of AP and EO are both explorative in *Doing*. Hence, the new technologies introduced by MT are possibly adopted in their production in an exploratory manner. The technology reflected in the product feeds back into the R&D through market selection, creating a virtuous cycle that reduces the risk of evolutionary adaptation caused by MT. Therefore, AP and EO types play a positive role in enhancing technological diversity by adding a high degree of novelty through MT to technological evolution.

Finally, Model 5 presents the result for the interaction of PO with HGT. In contrary to all previous results of positive (+) relation, HGT by PO types affect negatively (-) to technological diversity. This indicates the nature of HGT performed by PO type is different from others. Specifically, HGT increases technological diversity by making the distribution of technologies (IPC codes in this study) uniform within a taxon through the introduction of new technologies. However, when resulting in skewing the distribution of technologies, HGT may affect diversity negatively. PO types are firms with exploitative routines in both *Knowing* and *Doing*. According to Schumpeter's typology, they are "hedonic-static actors who essentially do what they have learned (Schumpeter, 1911: 542)." Therefore, from a sectoral perspective on overall technologies, they search for the deepening or substitution of existing technologies despite HGT, rather than for new technological combinations not existed in sector. Therefore, the technologies that PO type firms search for through the HGT pattern will be biased toward specific technologies associated with existing technologies, negatively impacting the level of technological diversity.

To summarize, the pattern of technological evolution is differentiated by innovation routines, and thus routines can affect diversity dynamics in technology. more specifically, among the four types of innovation routines identified in this work, AA types have significantly positive relation with technological diversity. Especially, HGT performed by

AA types increases the level of technological diversity. In addition, the results demonstrate that the relationship between technological search and diversity changes depending on the routine of the firm. The effect of organizational routines on technological diversity prioritizes technological search as a driver of the diversity dynamics concluded in Chapter 5. In other words, organizations act as a micro-criteria to technological diversity dynamics, suggesting that routines making decisions prior to technological search affect technological evolution of entire sector.

6.5 Sub-conclusion

This chapter aimed to investigate the dynamics of technological diversity on organizational routine, given the hypothesis that routines play a role in determining the technological search discussed in Chapter 5.

The first step of the study is to identify and categorize organizational routines. A firm's organizational routines can be identified through observable behaviors. Routine is a concept with a high level of complexity and should be derived through multi-dimensional behaviors rather than single actions. This study attempts to identify innovation routines through a two-dimensional approach to a firm's *Knowing* and *Doing*. To this end, with exploration and exploitation as indicators, each year of the analysis period measures the extent to which each firm wants to be innovative (willingness for novelty). By comparing their average values within the sectoral regime where firms under the same environmental change and selection pressure gather, the innovation routine is categorized into four types:

active pioneers, efficient optimizers, passive observers, and adaptive explorers.

For the next step, based on the innovation types of photovoltaic firms, we investigate their relationship with the technological evolution and diversity dynamics on overall photovoltaic technologies as discussed in Chapter 4. The evolutionary patterns of each innovation types are examined on the evolutionary phylogenetic tree and then regression analysis is performed. The results of the analysis are summarized below.

First, the results of the empirical analysis of 19 photovoltaic firms indicate that the routine quantification method proposed in this study is effective in identifying routine as a unique characteristic of a firm. The innovation routine of each firm has not changed significantly over time. Despite the dynamics of the photovoltaic industry observed during the analysis period, firms continued to repeat their existing routines and adhered to innovation patterns. These results show the unanimous consensus of scholars regarding the nature of routine and recurrence (Becker, 2004, 2005b; Cohen et al., 1996). Meanwhile, some firms such as Kyocera, Fuji Electric, and Hanwha have gradually changed their routines and adapted to the environment. Their routines move gradually every year, leading to changes in the type of innovation in the firm. Previous studies have revealed that this routine change progresses gradually over a long period of time based on past results (Becker et al., 2006; Cohen et al., 1996; Levitt & March, 1988). This is because rapid changes can be unfavorable for adaptation to the existing environment (Bowonder et al., 2010; Kardong, 2005). Bosch Solar Energy suggests that a radical change in routine is related to the life and death of the firm. Each firm has aspects of its innovation routine that differentiate it from other firms, even if they belong to the same type. In other words, each firm has its own direction for endogenous routine changes, which means that there is a possibility that the heterogeneity of firms will increase or become homogeneous over a long period.

Second, organizational routines affect the patterns of technological evolution. The result shows that the evolutionary patterns of overall photovoltaic technologies reflect the characteristics of firms' innovation routine types. In addition, the results of the regression analysis with diversity dynamics support organizational routines as a factor in the endogenous mechanism of technological diversity dynamics. AA types confirm a significant positive relationship with technological diversity, especially when combined with the HGT pattern of technological search. Such result further emphasizes the importance of combinatorial innovation derived in Chapter 5. We also found that the two types of exploratory innovators in *Doing*, AP and EO types, contribute to the overall increase in technological diversity by performing the MT pattern of technological search, which previously did not show significant relationship with diversity. Meanwhile, the HGT pattern of technological search, which has been significantly positive in all previous analyses, tend to reduce the overall technological diversity when performed by PO types. The results suggest that the organizational routine for making decisions prior to technological search affect the dynamics of technological diversity as micro-criteria.

Chapter 7. Conclusion

7.1 Summary of the Study

What is the endogenous mechanism behind technological diversity dynamics? To answer this question, which have not been fully explained in previous literature, this study quantitatively identifies the general endogenous mechanisms of technological diversity in terms of technological search and organizational routines. Additionally, an evolutionary phylogenetic tree methodology, commonly used in biology and product evolution studies, is applied to identify technological trajectories, and examine diversity dynamics across these trajectories. The significance of this study is that the evolutionary phylogenetic tree of technology is a methodology that considers the process of technology evolution and compensates for the limitations of previous comprehensive approaches to technological diversity. The empirical analysis focused on the photovoltaic technology. the case selection is based on the importance of photovoltaic technology for sustainability, and the ease of interpretation provided by the industrial dynamics and technological classification in photovoltaics. Given the key role in the energy portfolio, continued innovation is essential. Through the understanding diversity dynamics from an evolutionary perspective, this study aims to provide a generalized framework for the endogenous mechanisms of technological diversity. Then based on this, the study derives practical and pragmatic suggestions for the of the further development of photovoltaic technology.

Chapter 2 reviews previous literature on diversity, technological search, and organizational routines drawing on the theory of evolution and evolutionary economics as the academic foundation of this research. It also introduces the evolutionary phylogenetic methodology to construct the evolutionary space of technologies and identify detailed technological trajectories. The conceptual framework of endogenous dynamics in technological diversity, proposed in this study, is derived from this theoretical and methodological background. The study examines technological search and organizational routines as internal factors influencing technological diversity dynamics. Technological search is hypothesized to be a driver of diversity that directly creates and modifies diversity, while organizational routines act as micro-criteria for diversity dynamics by making decisions about technological search.

Chapter 3 provides a review of photovoltaic technologies, industries, and markets, which are subject to empirical analysis. First, it describes the rationale for selecting the case study, which is based on global expectations and challenges related to carbon emission reduction and sustainability in photovoltaic technology. Next, an overview of photovoltaic technology and historical facts regarding industry and market changes are presented to provide a better understanding of the empirical analysis.

In **Chapter 4**, the technological evolution and the dynamics of technological diversity are observed using an evolutionary phylogenetic methodology. The analysis employs data from 8,081 photovoltaic technology patents granted by the USPTO from 2000 to 2018, along with the subgroup IPC codes included in each patent. Entropy, a measure of diversity from information theory, is used to evaluate the information in the constructed evolutionary phylogenetic tree. The results of the evolutionary phylogenetic tree and diversity measures of photovoltaic technologies presented in Chapter 4 served as the basis for the subsequent analyses in Chapters 5 and 6.

The observed phenomena in the evolutionary phylogenetic tree of photovoltaic technology derived in this chapter fit well with actual historical facts. Technological evolution in photovoltaics follows a gradual pattern, with first-, second-, and third-generation technologies forming their own trajectories. The diversity of photovoltaic technology gradually increases during the evolutionary process. However, there is a discrepancy between the overall and trajectory-specific levels of diversity measurement, indicating that examining diversity by technology trajectory is necessary to understand the evolution of specific technologies. Furthermore, based on the information in the evolutionary phylogenetic tree and the diversity results, the subsequent evolution of the major trajectories as of 2018 is predicted. According to the result, the trajectory of the first-generation technology is at risk of extinction, while the trajectories of either the mixed first- and second-generation or the third-generation are expected to be retention. However, the trajectory of the third-generation technology needs to be supplemented because its small population increases its evolutionary risk. Meanwhile, both in aggregate and within trajectories, the diversity of photovoltaic technology has stagnated or declined since 2015. This suggests a weakening of the current innovation momentum in photovoltaic technology, as technological diversity serves as a stimulus and indicator of innovation as well.

Chapter 5 focuses on the relationship between diversity dynamics and technological search, which is characterized by three patterns from an evolutionary perspective: vertical inheritance (VI), horizontal gene transfer (HGT), and mutation (MT). The empirical analysis in this chapter uses the same data as in Chapter 4, and regression analysis is performed.

The evolution of photovoltaic technology mainly involves technological search in the VI pattern, while the HGT pattern is the least common. This indicates that photovoltaic technology pursued incremental innovation within the existing trajectories and lacked new technology combinations through cross-trajectory exchange. Regression analysis revealed a statistically significant relationship between technological diversity and two patterns of technological search, VI and HGT, with a decreasing and increasing effect, respectively. However, the search of MT is not significantly related to diversity. Furthermore, the greater the range of ancestral technologies, whether direct or neighboring, the higher the level of diversity in the descendants. These result hold across time periods, confirming that the relationship between technological diversity and technological search is endogenous, independent of temporal or external factors.

The results in Chapter 5 indicate that a significant increase in technological diversity occurs by recombining technologies from neighboring ancestors identified in the evolutionary phylogenetic tree of technology. In other words, this implies that the principle of increasing technological diversity is to gradually expand the evolutionary space by recombining with other technologies to the extent that technological relatedness exists.

Finally, **Chapter 6** examines the relationship between organizational routines and diversity dynamics, and by extension, technological search patterns. This work uses granted patent data from USPTO and photovoltaic module data from PVsyst version 6.0 for the period 2000 to 2022. This chapter is divided into two parts: i) identifying and categorizing routines, and ii) examining the relationship between routines and diversity.

In the first part, organizational routines, which are inherent to an organization, are identified as externally observable behaviors of the firm. Because routines are highly complex, they should be approached as multidimensional behaviors rather than a single behavior. This study takes a two-dimensional approach to *Knowing* and *Doing* to derive innovation routines for firms. The indicators of exploration and exploitation measures the extent to which firms are willing to be novel in each behavior, and their mean values are compared within the sectoral regime to classify them into four types: active pioneer (AP), efficient optimizer (EO), passive observer (PO), and adoptive adventurer (AA).

The empirical analysis of 19 photovoltaic companies confirmed that the quantification method of routines proposed in this study is a valid to identify routines as unique characteristics of firms. Each firm adheres to its existing innovation routines despite changes in the external environment, and some of the changes in routines occur gradually over time. It is also observed that even firms belonging to the same type of routines have their own unique aspects of innovation routines. The results suggest that each firm has its own distinctive orientation to endogenous changes in routines, which may lead to variation of heterogeneity within sectors over time.

In the second part, this study explored the relationship between each type of innovation routine and diversity dynamics through regression analysis. The results showed that organizational routines affect technology evolution. In addition, by observing the pattern of photovoltaic technology evolution by innovation routine type, the characteristics of each type are reflected in the evolutionary process in the overall photovoltaic technology.

The regression results support organizational routines as a factor in the endogenous mechanism of technological diversity dynamics. Among the four types of innovation routines, the AA type showed a statistically significant effect on the overall increase in technological diversity. Specifically, technological diversity is increased when this type performs the HGT pattern of technological search, further emphasizing the importance of combinatorial innovation derived in Chapter 5.

To identify a more detailed relationship, each interaction between the four types of innovation routines and the three patterns of technological search is confirmed (a total of twelve interactions). The results show that the relationship between technological search and diversity changes depending on firm's routine. Specifically, it is inferred that the MT pattern of technological search which was not significantly related to diversity in previous analyses, has the effect of increasing overall technological diversity when performed by AP types and EO types. On the other hand, it was confirmed that the HGT pattern of technological search, which showed a significant positive relationship in all previous analyses, tends to reduce the overall technological diversity when performed by PO types. The conclusion of Chapter 6 is that the organizational routines that make decisions prior to technological search affect the dynamics of technological diversity as micro criteria.

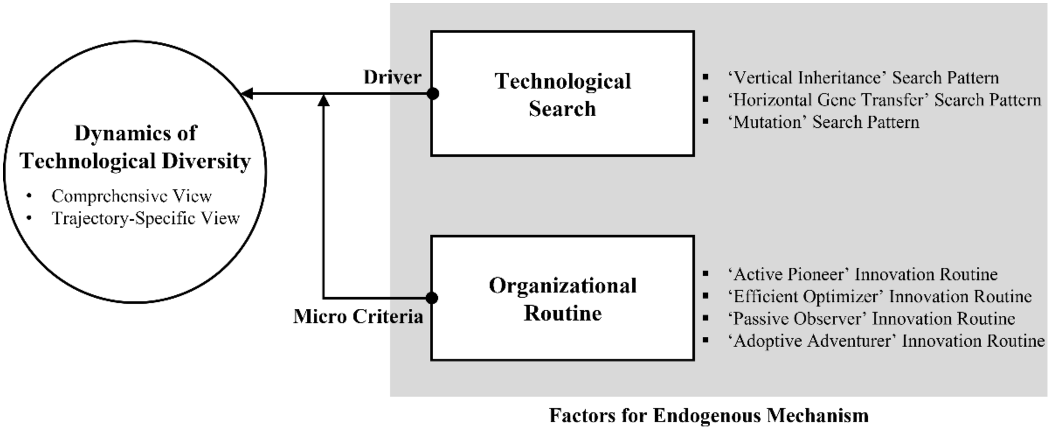


Figure 7-1. Endogenous dynamic of technological diversity in terms of technological search and organizational routines

The results of the study are summarized in **Figure 7-1**. The dynamics of technological diversity should be examined by identifying specific trajectories, not just by considering technology as a whole. In addition, for the endogenous dynamics of technological diversity, technological search and organizational routines are internal factors. Technological search drives dynamics of technological diversity, and organizational routines act as micro criteria for this process.

7.2 Implications and Limitations

7.2.1 Practical Implications

Technological diversity allows the exploration of new possibilities, promotes adaptation to changing environments and contributes to the long-term development of industries and economies. Maintaining a certain level of technological diversity is essential to attract the expansion of the knowledge base and spillovers, and to generate innovation through cross-technology recombination. To be sure, technological diversity may be reduced at certain times, such as when production efficiency is emphasized, and market stabilization requires standardized technologies. It is also possible that firms, especially those driven by returns to scale, may not be as proactive in increasing technological diversity.

This study has consistently maintained the evolutionary economics position that technological diversity generally plays a positive role in promoting innovation. For long-term sustainable development, policy makers should promote technological diversity[46]. Moreover, the empirical case of photovoltaic technology shows that technologies evolve by interacting with the external environment. In the face of change and uncertainty, technological diversity provides a means of responding flexibly and building resilience.

The empirical findings of this study on endogenous dynamics of technological diversity have strong implications for government policies and firm strategies to maintain and increase technological diversity.

First, for the design of policies and strategies, it is necessary to understand the overall evolution of the technology, while simultaneously identifying the evolutionary patterns of specific trajectories. The differences in evolutionary patterns across trajectories found in this study highlight the importance of analyzing specific trajectories rather than making generalizations about the entire sector. The Car Allowance Revate System (CARS), also

[46] Discussing the appropriate level of technological diversity is beyond the scope of this study and is left to future work.

known as the Cash-for-Clunkers program, is an example of a failed policy instrument that did not take technological trajectories into account. This program is a government initiative implemented around 2009-2010 in several countries, including the United States, Germany, the United Kingdom, and France, to revitalize the automotive industry, stimulate economic activity, and reduce carbon emissions. While the specifics varied from country to country, the general idea was to provide financial incentives to consumers who traded in older, less fuel-efficient vehicles for newer, more fuel-efficient models. However, the program is considered to have failed to achieve its environmental and economic goals (Klier & Linn, 2011). Reasons for the failure include not incorporate vehicle life cycles and potential backlash effects, as well as ignoring the detailed technological trajectory of automotive innovation, namely the rapid technological development of hybrid and electric vehicles (Naumov et al., 2023). There are even more examples of corporate strategies that failed because they didn't take technology trajectories into account.[47] By considering detailed trajectories as well as overall patterns of technological evolution, it is possible to identify promising technologies to allocate resources more effectively and, conversely, to develop targeted interventions to promote the adoption of technologies that have lagged behind despite their potential. It can also help prevent technological lock-in caused by a focus on specific technologies.

Second, combinatorial innovation is beneficial to the extent that it is technically feasible,

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[47] For examples, Kodak lost share in the camera industry because it failed to read the paradigm shift from analog to digital and the new trajectory of the camera market. Nokia, on the other hand, despite being the first to develop smartphones and tablet PCs, ended up with a weak presence in the market due to a lack of commercialization judgment and timing.

rather than the introduction of entirely new technologies. The endogenous mechanism of technological diversity revealed by this study is that technological diversity increases significantly when one technology is recombined with other related technologies. Scholars have long recognized combinatorial innovation as a powerful source of novelty (Gilfillan, 1935; Usher, 1954; Fleming, 2001; Hargadon & Sutton, 1997). Recombining different technologies can produce new and useful solutions to complex problems. However, not all cases of recombination lead to success because the process of recombination is inherently uncertain. Factors such as compatibility, selection pressure, and the operating environment influence the outcome of recombination, much like the uncertain nature of species in evolution. Contrary to common misconceptions about innovation, the introduction and combination of entirely new technologies poses evolutionary risks in terms of adaptability and efficiency. Consider the example of Amazon's Fire Phone, introduced in 2014. It incorporated new technologies that hadn't existed in mobile phones before, such as 3D display, but failed to make much of a splash in the market due to its high price and limited app ecosystem. While reuniting with a mutant technology may seem highly innovative, the failure to adapt to the market highlights the risks involved. Conversely, recombination between related technologies has distinct advantages for innovation. Related technologies share a degree of compatibility that reduces the potential risks and uncertainties of recombination. Such recombination also makes them easier to adopt and integrate into existing systems (Christensen, 2013; Garud et al., 1997). To facilitate this approach, interdisciplinary collaboration can be encouraged through research funding programs, networking events, and open innovation initiatives. Public-private collaboration platforms and incentives for industry-academia collaboration can further promote combined innovation in related technologies. To promote combined innovation, public policies can strengthen technology transfer programs and streamline licensing procedures. Providing funding for transfer costs and enhancing access to existing technologies can incentivize innovators while smoothing the path to innovation. Initiatives such as the European Union's Horizons 2020 and the United Kingdom's Innovate UK are examples of policies and programs to encourage combinatorial innovation[48].

Third, customized strategies and policy portfolios are needed that take into account firm- or group-specific characteristics. This study quantitatively derives the organizational routines of photovoltaic firms and identifies the heterogeneity within the industry. It then concludes that this heterogeneity affects the endogenous dynamics of technological diversity in different ways.

Organizational routines are inherent characteristics that underpin firm stability and gradual change. These routines build on accumulated knowledge, capabilities, and past successes and shape how tasks are performed, knowledge is shared, and resources are

[48] Horizon 2020 is the European Union's research and innovation funding program that ran from 2014 to 2020. With a budget of approximately €80 billion, it was the largest EU research and innovation framework program ever, focusing on (1) funding researcher-led projects through the European Research Council (ERC) and supporting researcher mobility and training through the Marie Sklodowska-Curie action; (2) building Europe's industrial leadership by supporting research and innovation in key sectors and strengthening the competitiveness of SMEs; and (3) encouraging interdisciplinary collaboration and partnerships to address societal challenges. Meanwhile, Innovate UK is an executive non-departmental public body funded by UK Research and Innovation (UKRI). Innovate UK focuses on providing funding, connecting businesses with expertise and resources, and facilitating collaboration between businesses, research institutions and other stakeholders. Each of references are the websites of Horizon 2020 and UKRI, respectively.

allocated. By incorporating routines into strategy formulation, managers can facilitate learning and resource allocation reliably and efficiently. When organizational routines are not considered, market relevance can decline due to loss of focus and differentiation. The story of Yahoo, once a dominant Internet company, illustrates not only the importance of identifying and adjusting one's own organizational routines to remain competitive and relevant, but also the dangers of rapid change and blind replication of routines. To compete with Google, Yahoo overlooked its own strengths, such as its existing presence in web portals, news, and email services, and blindly copied Google's search engine and advertising strategy, losing its own identity and market share.

Policymakers should also consider the organizational routines that produce heterogeneity. In a situation where individual firms are different from each other and their groups have heterogeneous characteristics, policy attempts to satisfy all firms with the average by assuming a representative firm are unlikely to succeed. Therefore, the existence of heterogeneity must be taken into account when designing policies for firms in order to maintain a balance between promoting innovation and ensuring responsible development, and to improve the effectiveness of policies without alienating policy consumers.

By recognizing the importance of firm-specific routines and heterogeneity, and adopting tailored strategies and policies, policymakers and managers can create an enabling environment for innovation and growth. Understanding the stability and endogenous change inherent in routines allows for the development of targeted interventions and support mechanisms that match the unique characteristics of firms and industries.

7.2.2 Suggestions for Photovoltaic Technology

This study suggests the following implications for the current and future directions of photovoltaic technology.

First, photovoltaic technology has experienced a decline in diversity and search dynamics since 2015. Diversity is a necessary condition for the evolutionary mechanism to operate (Basalla, 1988). Such a decrease in diversity implies that the driving force of photovoltaic technology development has weakened. This study points out that contemporary photovoltaic technology is biased toward vertical inheritance, pursuing incremental innovation within the trajectory of existing technologies, and is least likely to pursue horizontal gene transfer seeking new technology combinations.

A clue to photovoltaic technology lies here. Technological diversity should be promoted through recombination of related technologies, including technologies that have already been developed and currently exist within the photovoltaic industry.

More specifically, the integration of technologies, regardless of generation, to realize high-efficiency photovoltaic cells, such as IBC cells, SHJ cells, TOPCon cells or silicon-based tandem photovoltaic cells, is the correct direction to pursue according to technological trajectories. First and second-generation mixed technologies must be included in the selection process, in order to create the dominant design with the highest diversity level. The drastic drop in the diversity level observed in the first-generation technologies that enjoyed market leadership thus far disproves the notion that current photovoltaic technology is in a technological transition period.

Lab-scale innovations in third-generation technologies can also quickly secure practicality by “standing on the shoulders of giants.” For example, perovskite technology faces many barriers to market entry, as it is classified as an emerging technology. This, despite its high potential and unprecedented photoelectric conversion efficiency improvement from 10% in 2012 to 25% in 2019. The time taken to secure technological maturity can be accelerated through convergence with existing technologies in which the technological foundation is well understood as well as mass production is stabilized. Recently, the tandem structure of perovskites on crystalline silicon substrates has shown a 31.3% technological advance (National Renewable Energy Laboratory, 2022). In addition, efforts are ongoing to apply the roll-to-roll method for mass production of thin-film solar cells (Kim et al., 2020; Rajagopal & Jen, 2018; Williams et al., 2016). Such convergence contributes greatly to diversity in photovoltaic technology by simultaneously increasing the technological scope and depth. This technological diversity enhances the flexibility of the system and increases the likelihood of finding better solutions in response to uncertainty (Stirling, 2010). In summary, for third-generation technology, it is appropriate to use existing technologies to increase diversity and improve practical completeness, and then derive a dominant design using this as a stepping-stone.

Second, to promote innovation and production on photovoltaics, relevant policies should consider firm heterogeneity and characteristics. Thus, this study sheds light on and confirms the existence of heterogeneity through the innovation routines of companies in the photovoltaic industry. The Adaptive Adventurer (AA) type dominates the innovation routines of the nineteen photovoltaic firms analyzed in this study. The predominance of the AA type, significantly related to increasing technological diversity, can be interpreted as a positive sign for photovoltaic technology innovation. Moreover, the MT pattern of technological search performed by AP and EO types is found to be effective in reducing the risk of evolutionary adaptation in new technologies and introducing a high level of novelty to the sector. Therefore, policy should support these firms to continue pursuing technologies that do not exist in the sector and ensure that the technologies they introduce are diffused, allowing other firms to expand the sector-wide technology space through technological search in the HGT pattern.

While photovoltaic firms are heterogeneous in their *Knowing* related to R&D, they are more homogeneous in their *Doing* related to production. Specifically, the production activities of the photovoltaic industry are generally exploitative. From a government viewpoint, such homogeneity of firms is favorable for achieving policy goals and improving the efficiency and effectiveness of policy instruments. However, an exploitative disposition to production is not beneficial from an innovation perspective. Unlike other actors for technology development, companies serve as intermediaries between technology and the market. This means that when firms continuously receive feedback on market responses to technology and organically link R&D and production, innovativeness across sectors will grow. Despite the development and growth of photovoltaic technology as a localized power source, the current concentration on utility-scale applications reflects an exploitative routine in the *Doing* of photovoltaic firms[49]. The IEA (2022) predicts that utility-scale photovoltaics remains a competitive source; however, the deployment of large-scale installations will become increasingly difficult due to a lack of suitable locations. It also points to the need to increase support for all sectors of photovoltaics and parallel development of on- and off-grid photovoltaics to align with the net-zero carbon scenario milestone.

This broadening of photovoltaic module applications is based on existing photovoltaic cell technologies, and thus aligns with the principle of increasing technological diversity mentioned earlier. Diversifying applications by developing modules with flexible, stretchable, or transparent characteristics based on second- and third-generation technologies featuring substrate freedom will lead to increased technological diversity. Recently, the rapid development of electric-powered transportation and wearable devices has expanded the applications of photovoltaic technology. Therefore, the government should provide a scheme to broaden the application of photovoltaic technology to create a virtuous cycle of innovation in technology and products.

7.2.3 Contributions and Limitations

This study extends the scholarly discussion on the endogenous dynamics of technological diversity by empirically examining technological search and organizational

[49] As of 2021, utility-scale plants account for 52% of global solar capacity, while residential accounting for 28% and commercial and industrial for 19%, respectively. Decentralized (off-grid) applications account for only 1%.

routines based on evolutionary economics. More specifically, by classifying technological search into specific patterns based on evolutionary concepts in biology, the explanatory power of technological search for the development of technology is enhanced. In addition, this study measures, identifies, and classifies organizational routines, which are key concepts in evolutionary economics. It is of academic significance that organizational routines, an abstract and complex concept inherent in firms, are empirically analyzed through a multidimensional approach and relative comparison.

This study is particularly noteworthy for its use of an evolutionary phylogenetic methodology, which employs data-driven analysis facilitated by algorithms. The application of this methodology holds a pivotal position in hypothesis testing within the study, which inherently adopts an evolutionary approach. The absence of this methodology would have posed significant challenges and limitations, hindering the comprehensive exploration and understanding of the endogenous dynamics of technological diversity.

As a practical implication, this work evaluates the current state and provides practical advice on the future direction of photovoltaic technology. However, this work also has some limitations.

First, this study aims to derive a generalizable framework for the endogenous mechanisms of technological diversity. However, it is based on an empirical analysis of a specific case, photovoltaic technology. Although the study describes the rationale for the case selection, the framework needs to be strengthened for generalization through further research on other industries. Technological and industrial dynamics are influenced by a variety of situational contexts and are heterogeneous from others. Therefore, a more robust and generalized theory of the endogenous dynamics of technological diversity should be developed through comparative studies of different technologies.

Second, this study focuses on the mechanisms by which technological diversity is generated and changed, and identifies the patterns of technological search and organizational routines as factors. However, it is likely that there are other factors besides these two factors in the endogenous mechanism of technological diversity. This study also found that different patterns of technological search have heterogeneous effects on technological diversity, but it did not identify under what contextual circumstances different patterns of technological search are used. Therefore, further research should be conducted to solidify the discussion on technological diversity.

The third is to validate the evolutionary phylogenetic tree of technology. Although the technological evolutionary tree is a quantitative and scientific construct based on data and algorithms, its validation using a qualitative approach is limited. This study attempted to compensate for this by using keywords to describe key taxa that are nodes of the phylogenetic tree, but it is still insufficient. This limitation is also pointed out by J.-D. Lee et al. (2022). The taxa-level phylogenetic analysis used in this study is an appropriate method for observing the macroscopic flow of technological evolution. Conversely, the currently constructed phylogenetic tree of technological evolution has limitations for quantitative analysis at the micro level. One way to overcome this limitation is to represent the unit of analysis, i.e., technology, as a smaller micro-level unit than taxa, thus increasing the number of observations for analysis. Future research could address this limitation by applying various embedding techniques from machine learning to transform technologies into analyzable objects. Alternatively, probabilistic models can be integrated into network analysis frameworks, such as Bayesian networks, to attempt statistical analysis and prediction. This approach allows dealing with uncertainty through probabilistic models and simultaneously understanding of evolutionary relationships between technologies and structural aspects of technological evolution through networks. Therefore, the development of quantitative and objective metrics and model frameworks should be further explored in future studies.

The last one relates to the data aspect. On the one hand, photovoltaic patent and module data have fundamental limitations as proxies for technology and product, respectively. Therefore, further empirical analysis should be conducted on more technologies and products to solidify the theoretical discussions. On the other hand, due to data limitation, only nineteen firms are empirically analyzed in Chapter 6. Specifically, Chinese firms, which are major players in the photovoltaic industry, are not included in the analysis. Therefore, there are restrictions in interpreting the results as a holistic view of trends for the photovoltaic industry. No dataset can ever be a perfect representation of the diverse and complex real world. This is an inevitable limitation of any researcher conducting quantitative analysis using data as a proxy for reality. However, it is expected that subsequent efforts to improve the quantity and quality of data through continuous data construction will improve the relevance of quantitative analysis results to reality.

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Appendix I. Robustness Check

A I. i Robustness Check for Chapter 5

The ordinary least square (OLS) model with the addition of both period dummies and interaction terms for search and period to reflect heterogeneous selection pressures (exogeneous changes) across years, is shown in Equation A-1. The model uses technological diversity measured by information entropy as the dependent variable and the other variables in Table 5-1 as explanatory variables.

$$\begin{aligned} TD_{jt} = \beta_0 + \beta_1 VI_{jt} + \beta_2 HGT_{jt} + \beta_3 MT_{jt} \\ + \sum_k \beta_k \, Control\ Variables_{kt} \\ + \sum_p \beta_p \, Period\ Dummy_p \\ + \beta_m^{VI} Period\ Dummy_p VI_{jt} \\ + \beta_m^{HGT} Period\ Dummy_p HGT_{jt} \\ + \beta_m^{MT} Period\ Dummy_p MT_{jt} + \varepsilon_{jt} \end{aligned} \qquad \text{Eq. (A-1)}$$

$Period\ Dummy_p$ refers to the period-specific dummy, which has a dummy value of period 1 if t is 2000~2004, period 2 if t is 2005~2008, period 3 if t is 2009~2013, and period 4 if t is 2014~2018 according to the criteria of periods presented in Table 3-2. Then the interaction effects of each time period and the three patterns of search are estimated (β_m^{VI}, β_m^{HGT}, β_m^{MT}).

First, to check the robustness of the original regression, the results of a pooled OLS with period dummies are shown in **Table A1**. In Model 5, which utilizes all-period dummy variables to capture the effect of all periods, VI has a negative effect on technological diversity, HGT has a positive effect, and MT is not significantly correlated. These results are in line with those in Table 5-4, suggesting that the technological search has a consistent effect on technological diversity.

Second, **Table A2** present the regression results for the interaction terms. Each of search patterns has a consistent relationship with technological diversity regardless of the addition of period dummies and interaction terms. In particular, the interaction terms are not significantly correlated with technological diversity, indicating that the effect of technological search on technological diversity is not differentiated by period. In other words, the technological search is an endogenous determinant of technological diversity, even after accounting for heterogeneity in period.

Table A1. Result of regression (Robustness check for Chapter 5)

Dependent variable: Entropy	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.093 (0.063)	-0.057 (0.064)	0.0092 (0.074)	-0.062 (0.076)	-0.056 (0.050)
Vertical Inheritance of Taxon	**-0.22**** **(0.080)**	**-0.21*** **(0.082)**	**-0.19*** **(0.084)**	**-0.18*** **(0.083)**	**-0.21*** **(0.080)**
Horizontal Gene Transfer of Taxon	**0.23***** **(0.063)**	**0.23***** **(0.064)**	**0.23***** **(0.065)**	**0.24***** **(0.065)**	**0.23***** **(0.062)**
Mutation of Taxon	-0.018 (0.062)	-0.036 (0.064)	-0.051 (0.064)	-0.054 (0.064)	-0.021 (0.062)
Gene Pool Size	**0.26**** **(0.087)**	**0.31***** **(0.088)**	**0.29**** **(0.090)**	**0.25*** **(0.097)**	0.16 (0.10)
Global Gene Pool Size	**0.25***** **(0.070)**	**0.40***** **(0.072)**	**0.34***** **(0.068)**	**0.28***** **(0.079)**	0.099 (0.12)
Number of patents in Taxon	**0.49***** **(0.10)**	**0.47***** **(0.10)**	**0.47***** **(0.11)**	**0.49***** **(0.11)**	**0.53***** **(0.10)**
Period 1 Dummy	**-0.53**** **(0.18)**	-	-	-	**-0.60***** **(0.18)**
Period 2 Dummy	-	0.31 (0.17)	-	-	-0.057 (0.16)
Period 3 Dummy	-	-	-0.024 (0.13)	-	0.11 (0.10)
Period 4 Dummy	-	-	-	0.24 (0.19)	**0.49*** **(0.21)**
Number of Obs.	103	103	103	103	103
Adj R-squared	0.69	0.68	0.67	0.67	0.70

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Table A2. Result of regression for interactive variables (Search*Period)

Dependent variable: Entropy	Model 6 Period 1*Search	Model 7 Period 2*Search	Model 8 Period 3*Search	Model 9 Period 4*Search
Intercept	**0.382*** **(0.173)**	-0.054 (0.062)	0.010 (0.073)	-0.063 (0.077)
Vertical Inheritance of Taxon	-0.179 (0.101)	-0.121 (0.091)	-0.193 (0.108)	**-0.181*** **(0.086)**
Horizontal Gene Transfer of Taxon	**0.857**** **(0.285)**	**0.152*** **(0.070)**	**0.175**** **(0.072)**	**0.233***** **(0.066)**
Mutation of Taxon	1.220 (0.790)	-0.023 (0.062)	-0.045 (0.063)	-0.054 (0.064)
Gene Pool Size	**0.354***** **(0.087)**	**0.327***** **(0.086)**	**0.294***** **(0.088)**	**0.256*** **(0.111)**
Global Gene Pool Size	**0.391***** **(0.082)**	**0.373***** **(0.070)**	**0.368***** **(0.067)**	**0.255**** **(0.085)**
Number of patents in Taxon	**0.398***** **(0.105)**	**0.418***** **(0.104)**	**0.453***** **(0.104)**	**0.522***** **(0.114)**
Period Dummy	-0.154 (0.337)	0.240 (0.168)	0.093 (0.131)	-4.550 (4.252)
Period Dummy * VI	0.454 (0.513)	-0.112 (0.167)	-0.080 (0.142)	-0.028 (0.161)
Period Dummy * HGT	-1.235 (0.678)	0.252 (0.174)	0.262 (0.181)	-1.510 (1.545)
Period Dummy * MT	1.531 (1.314)	0.914 (0.559)	0.820 (0.471)	-18.792 (18.313)
Number of Obs.	87	103	103	103
Adj R-squared	0.740	0.698	0.684	0.667

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

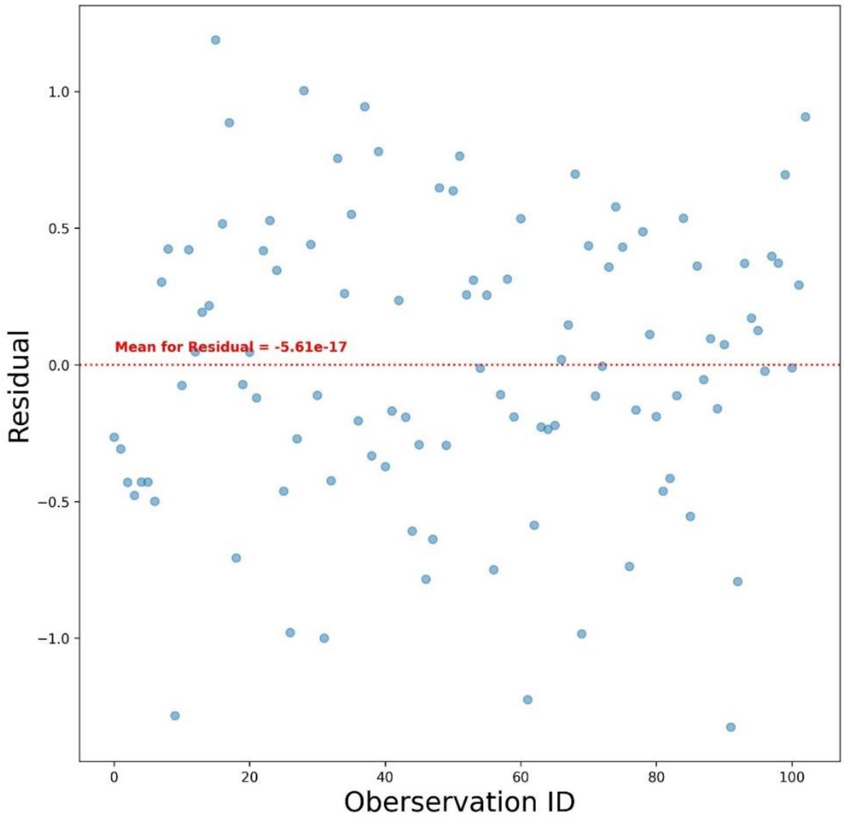

Figure A1. Result of residual analysis

Figure A1 is the residual scatter plot for Model 5. The mean of the residuals is virtually zero (-5.61 e-17) and is distributed in a random manner. Therefore, the results of the residual analysis can be considered to follow the Gauss - Markov Theorem, suggesting that linear estimation through the OLS method applied in this study is appropriate.

A I. ii Robustness Check for Chapter 6

The regression model to ensure the robustness of the routine regression presented in Chapter 6 is a pooled OLS model. Since the pooled OLS model does not control for the time-of-year effect that the traditional mixed regression model does, an additional analysis was performed in which the data was split into two time periods (Period 1 & Period 2; Period 3 & Period 4).

As shown in **Table A3**, the regression analysis performed by the pooled OLS method yielded the same results as the original results. In addition, while the periodized analysis resulted in consistent with the original results for HGT, some of the regression models for Period 1 & Period 2 (VI of Taxon, AA Dummy) showed different statistical significance from the original results (Table 5-1). This is expected to be due to the lack of observations. Meanwhile, the analysis to check the robustness of the interaction between technological search and organizational routine (see **Table A4**) also produced the same statistical significance and coefficient positive-negative trend as the original results, except for one variable in Model 7 (PO Dummy) (Table 5-2). From the results, it can be interpreted as confirmation of the robustness of the original regression results.

Table A3. Results of regression (Robustness check for Chapter 6)

Dependent variable: Entropy	Model 1	Model 1 for period 1 & 2	Model 1 for period 3 & 4
Intercept	**-0.326* (0.140)**	0.099 (0.958)	-0.016 (0.164)
Vertical Inheritance (VI) of Taxon	**-0.232** (0.084)**	-0.175 (0.289)	**-0.310** (0.102)**
Horizontal Gene Transfer (HGT) of Taxon	**0.267*** (0.065)**	0.168 (0.090)	**0.410** (0.136)**
Mutation (MT) of Taxon	-0.056 (0.061)	-0.003 (0.072)	0.588 (0.435)
Gene Pool Size	**0.358*** (0.087)**	1.669 (1.240)	**0.338*** (0.0874)**
Global Gene Pool Size	**0.363*** (0.070)**	0.245 (0.859)	0.366*** (0.106)
Number of patents in Taxon	**0.365** (0.132)**	0.056 (1.417)	0.429** (0.132)
Active Pioneer (AP) Dummy	0.194 (0.143)	0.550 (0.270)	-0.146 (0.174)
Efficient Optimizer (EO) Dummy	-0.083 (0.245)	0.415 (1.005)	-0.108 (0.248)
Passive Observer (PO) Dummy	-0.122 (0.134)	-0.098 (0.266)	-0.215 (0.157)
Adoptive Adventure (AA) Dummy	**0.420** (0.153)**	0.411 (0.311)	**0.611*** (0.180)**
Number of Obs.	103	37	66
Likelihood	0.695	0.319	0.687

Notes:

1. Standard errors are in parentheses.

2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5%levels, respectively.

3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Table A4. Results of regression for interactive terms

Dependent variable: Entropy	Model 2 AA * HGT	Model 3 AP * MT	Model 4 EP * MT	Model 5 PO * HGT
Intercept	**-0.291*** **(0.117)**	-0.081 (0.086)	0.020 (0.066)	0.195 (0.119)
Search of Taxon	0.065 (0.077)	0.018 (0.055)	0.042 (0.061)	**0.788*** **(0.314)**
Active Pioneer (AP) Dummy		**0.352**** **(0.133)**		
Active Pioneer * Search of Taxon		**1.71***** **(0.326)**		
Efficient Optimizer (EO) Dummy			0.259 (0.284)	
Efficient Optimizer * Search of Taxon			**2.743**** **(1.012)**	
Passive Observer (PO) Dummy				-0.231 (0.155)
Passive Observer * Search of Taxon				-0.607 (0.318)
Adoptive Adventurer (AA) Dummy	**0.398**** **(0.143)**			
Adoptive Adventurer * Search of Taxon	**0.301**** **(0.110)**			
Gene Pool Size	**0.471***** **(0.082)**	**0.347***** **(0.074)**	**0.348***** **(0.083)**	**0.389***** **(0.082)**
Global Gene Pool Size	**0.352***** **(0.063)**	**0.387***** **(0.068)**	**0.310***** **(0.067)**	**0.323***** **(0.064)**
Number of patents in Taxon	**0.165*** **(0.090)**	**0.308***** **(0.081)**	**0.408***** **(0.096)**	**0.320***** **(0.089)**
Number of Obs.	103	103	103	103
Adjust R-squared	0.713	0.643	0.663	0.719

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Appendix II. Interaction Result of Regression

Table A5. Interaction between Active Pioneer and search patterns

Dependent variable: Entropy	Model 1 VI	Model 2 HT	Model 3 MT
Intercept	-0.132 (0.117)	-0.137 (0.104)	-0.065 (0.100)
Search of Taxon	-0.110 (0.122)	0.105 (0.070)	0.025 (0.056)
Active Pioneer Dummy	0.288 (0.148)	**0.272*** **(0.135)**	**0.336**** **(0.128)**
Active Pioneer * Search of Taxon	-0.065 (0.143)	**0.242*** **(0.112)**	**1.674***** **(0.316)**
Gene Pool Size	**0.274**** **(0.090)**	**0.407***** **(0.078)**	**0.336***** **(0.073)**
Global Gene Pool Size	**0.258***** **(0.080)**	**0.284***** **(0.078)**	**0.382***** **(0.078)**
Number of patents in Taxon	**0.442***** **(0.111)**	**0.242**** **(0.083)**	**0.335***** **(0.078)**
Number of Obs.	103	103	103
Likelihood	-99.068	-93.829	-87.466

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5%levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Table A6. Interaction between Efficient Optimizer and search patterns

Dependent variable: Entropy	Model 1 VI	Model 2 HT	Model 3 MT
Intercept	0.058 (0.090)	0.023 (0.086)	0.021 (0.087)
Search of Taxon	**-0.177* (0.084)**	**0.162** (0.060)**	0.060 (0.063)
Efficient Optimizer Dummy	-0.166 (0.260)	-0.179 (0.239)	0.222 (0.272)
Efficient Optimizer * Search of Taxon	**-0.457* (0.202)**	**0.504* (0.227)**	**2.725** (0.978)**
Gene Pool Size	**0.240** (0.089)**	**0.387*** (0.080)**	**0.349*** (0.082)**
Global Gene Pool Size	**0.297*** (0.079)**	**0.310*** (0.077)**	**0.305*** (0.079)**
Number of patents in Taxon	**0.690*** (0.132)**	**0.401*** (0.092)**	**0.437*** (0.092)**
Number of Obs.	103	103	103
Likelihood	-97.411	-94.269	-96.463

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Table A7. Interaction between Passive Observer and search patterns

Dependent variable: Entropy	Model 1 VI	Model 2 HT	Model 3 MT
Intercept	0.047 (0.123)	0.195 (0.126)	0.006 (0.108)
Search of Taxon	0.003 (0.165)	**0.788** (0.304)**	0.031 (0.071)
Passive Observer Dummy	-0.017 (0.145)	-0.245 (0.144)	-0.012 (0.134)
Passive Observer * Search of Taxon	-0.190 (0.170)	-0.591 (0.307)	0.160 (0.131)
Gene Pool Size	**0.262** (0.091)**	**0.385*** (0.080)**	**0.329*** (0.084)**
Global Gene Pool Size	**0.284*** (0.081)**	**0.325*** (0.077)**	**0.297*** (0.081)**
Number of patents in Taxon	**0.511*** (0.108)**	**0.347*** (0.084)**	**0.397*** (0.090)**
Number of Obs.	103	103	103
Likelihood	-100.617	-94.837	-102.230

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Table A8. Interaction between Adoptive Adventure and search patterns

Dependent variable: Entropy	Model 1 VI	Model 2 HT	Model 3 MT
Intercept	-0.199 (0.275)	-0.255 (0.127)	-0.241 (0.139)
Search of Taxon	-0.062 (0.403)	0.072 (0.075)	0.126 (0.126)
Adoptive Adventure Dummy	0.296 (0.278)	**0.346* (0.139)**	**0.324* (0.152)**
Adoptive Adventure * Search of Taxon	-0.125 (0.399)	**0.303** (0.110)**	-0.066 (0.133)
Gene Pool Size	**0.308*** (0.092)**	**0.454*** (0.080)**	**0.393*** (0.087)**
Global Gene Pool Size	**0.342*** (0.080)**	**0.346*** (0.073)**	**0.326*** (0.081)**
Number of patents in Taxon	**0.424*** (0.109)**	**0.202* (0.087)**	**0.279** (0.093)**
Number of Obs.	103	103	103
Likelihood	-97.313	-91.375	-100.529

Notes:
1. Standard errors are in parentheses.
2. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.
3. Bold denotes statistical significance at the 0.1%, 1%, and 5% levels.

Abstract (Korean)

기술의 다양성(diversity)은 혁신의 자극제이자 지표이다. 다양한 기술의 존재 하에 재조합을 통한 혁신이 발생하고, 또 혁신의 결과로 차별화된 기술이 탄생하면서 기술이 다양 해진다. 경제의 발전 과정에서 기술 다양성은 증감 및 정체를 반복하며 끊임없이 변화한다. 기술 다양성의 역학은 기술과 산업의 성장 단계에 대한 정보를 제공하며, 정부 혁신 정책과 기업의 전략적 행동에 대한 근거로 활용된다. 그러나 기술 다양성과 그 역학(dynamics)이 갖는 이론적, 실천적 중요성에 비해 우리의 경험적 이해는 여전히 제한적이다. 선행연구는 기술 다양성을 산업과 같은 큰 범주에서 포괄적으로 측정하여 세부적인 기술 궤적에 대한 고려가 결여되어 있을 뿐 아니라 기술 다양성 역학의 내생적 메커니즘에 대해 충분히 설명하지 못한다.

기술 다양성과 그 역학에 대한 이론적 근거가 부재한 상황에서 혁신을 추진하고자 수행되는 기술 다양성 증가의 노력은 효율적이고 효과적인 결과를 불러오기 어렵다. 본 연구는 기술 다양성의 내생적 역학을 이해하여 보다 직접적이고 실천적인 혁신 정책 및 전략 방안을 찾고자 하였다. 이를 위해 다양성에 대한 진화적 관점에 주목하고, 진화경제학을 이론적 기반으로 한다.

보다 구체적으로, 기술다양성의 정량화에 진화계통도 방법론을 활용한다. 데이터와 알고리즘에 기반한 이 방법론을 통해 기술 진화 과정과 세부 궤적의 정보를 다양성 측정에 반영한다. 본 연구는 진화계통도 방법론을 연구 전반에 걸쳐 중요한 분석적 틀로 활용한다. 그리고 다양성 역학의 내생적 요인으로

기술 탐색과 조직 루틴을 지목한다. 이것은 기술 자체의 본질과 기술을 개발하는 행위자의 관점에서 기술 다양성 역학의 메커니즘을 규명하기 위한 접근이다. 실증 분석은 태양광 발전 기술을 대상으로 한다.

4장은 2000년부터 2018년까지 미국 특허청에 등록된 8,081개 태양광 기술 특허를 활용하여 태양광 발전 기술의 진화 계통도를 구축하고, 기술 발전 궤적을 도출한다. 기술 다양성의 정량화는 진화계통도에서 도출한 기술 궤적과 정보에 대해 정보이론의 엔트로피가 활용된다. 4장에서 도출된 기술진화계통도와 측정한 다양성의 정보는 이어 5장과 6장의 분석에서도 활용한다. 분석 결과로 도출한 태양광 기술 진화계통도는 태양광 기술발전의 실제 역사를 잘 설명하였다. 점진적 증가를 보인 평균적 다양성 추세와 달리 세부 기술 궤적은 보다 급진적인 변화가 존재했다. 한편 전체적 및 세부적 다양성 양상 모두 2015년을 기점으로 기술 다양성이 정체되거나 감소하는 경향이 관찰되어 현재 태양광 기술의 혁신 동력이 약화되고 있음을 발견하였다.

5장은 기술 자체의 본성에 관심을 두고, 기술 탐색에 대한 다양성 역학의 메커니즘을 살펴본다. 기술 탐색은 생물 진화의 개념에 근거하여 i) 수직적 전승(vertical inheritance), ii) 수평적 정보전달(horizontal gene transfer), 그리고 iii) 돌연변이(mutation)의 3가지의 패턴으로 분류하였다. 데이터는 4장과 동일하며, 다양성과 기술탐색의 관계 규명에 회귀분석이 수행되었다. 실증결과, 태양광 기술의 진화과정에서는 주로 수직적 전승 패턴의 기술 탐색이 확인되었고, 수평적 정보전달 패턴이 가장 적었다. 한편 수직적 전승과 수평적 정보전달의 탐색 패턴은 다양성과 통계적 유의미한 관계에 있고 각각 다양성을 경감 또는

증가시키는 것으로 나타났다. 그러나 다양성과 돌연변이 탐색과의 관계는 유의미하지 않았다. 5장에서 도출된 결과는 기술 탐색이 다양성 변화의 동인임을 지목한다. 즉, 기술 다양성은 기술 진화계통도에서 식별할 수 있는 이웃 선조의 기술요소를 재 조합함으로써 유의미한 증가가 발생한다.

6장은 기술개발의 행위자로서 조직 루틴과 다양성 역학의 관계를 고찰한다. 연구는 i) 루틴의 식별 및 유형화와, ii) 루틴과 다양성의 관계 규명의 2개 부분으로 구분된다. 먼저 다차원적 기업 행동을 통해 혁신 루틴을 식별하고, 산업내 상대비교를 통해 i) 활동적 개척자(active pioneer), ii) 효율적 최적화자(efficient optimizer), iii) 소극적 관찰자(passive observer), 그리고 iv) 적응형 탐험가(adoptive adventurer)의 4가지 유형으로 구분한다. 관계성 규명은 회귀분석을 수행하며, 2000년부터 2022년까지 미국 특허청 등록 특허와 태양광 시스템 시뮬레이션 프로그램인 PVsyst version 6.0의 태양광 모듈 데이터를 활용한다.

연구 결과 6장에서 제안하는 혁신 루틴의 정량화 및 유형화 방법은 기업의 고유한 특성인 루틴을 식별하는 유효한 접근임을 확인하였다. 또한 4가지 혁신 유형과 기술 다양성에 대한 회귀분석 결과를 통해 조직 루틴이 기술 다양성 메커니즘의 내생적 요인임을 밝혔다. 구체적으로 적응형 탐험가유형은 기술 다양성과 유의미한 양의 관계에 있으며, 특히 이 유형이 수평적 정보전달을 했을 때 전체 기술 다양성 증가에 영향을 미친다. 나아가 조직 루틴에 따라 기술 다양성에 대한 기술 탐색의 영향이 (5장의 결과) 변화하는 것이 확인되었다.

요약하자면, 기술의 탐색은 직접적으로 기술 다양성을 변화시키는 동인

(driver)이다. 이에 기반한 기술 다양성 증가의 원리는 기술적 연관성이 존재하는 범위 내에서 다른 기술과 재 조합하여 점진적으로 진화 공간을 확대시키는 것으로 도출되었다. 한편 조직 루틴은 기술 다양성 역학에 대한 미시적 기준(micro criteria)으로 작용한다. 조직 루틴은 기업의 기술 탐색 행동을 결정하며, 보다 구체적으로 기술 탐색의 방식과 범위, 정도를 결정한다. 결과적으로 기술 다양성은 조직 루틴에 기반한 기술 탐색 패턴에 의해 역동성을 가진다는 것이 본 연구가 제시하는 실증적 이론이다.

본 연구는 기술탐색과 조직 루틴을 기술 다양성 역학을 설명하는 새로운 지표로 제시하여 학술적 논의의 지평을 넓혔다는 것에 의의가 있다. 특히 진화적 관점에서 기술 탐색을 세분화하여 기술 탐색의 설명력을 높이고, 기업 행동에 대한 다차원적 접근과 부문(sector) 내 상대비교를 통해 조직 루틴을 식별하는 새로운 방법을 제시한다. 나아가 진화계통도 방법론은 기술 전반에 대한 통합적 접근을 취하였던 선행연구의 한계를 보완하고 동태적인 기술 발전 과정에 대한 이해를 확장하는데 기여한다.

마지막으로 본 연구의 결과는 기술 혁신을 유인하고 고무시키기 위한 기업 전략과 정부 정책적 측면에 효율성 및 효과성을 부여하는 역할로서 실천적 의의가 있다. 태양광 기술에 대한 실증분석 결과는 현재 직면한 산업의 현안에 대한 실리적이고 실제적 방안을 도출하는 과학적 근거가 될 것으로 기대한다.

주요어 : 진화경제학; 기술 진화; 다양성 역학; 기술 탐색; 조직 루틴; 태양광
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