DESIGN FOR GLOBAL SUCCESS

Unleashing Export Potential through Design and Facilitating International Design Collaboration through Air Connectivity

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Abstract

The significance of industrial design in shaping the world is increasingly acknowledged. This study aims to investigate the role of industrial design in economic growth, particularly in the context of a knowledge economy. To address this question, the study is divided into four main parts. In the first chapter, the global distribution of design patents is visually presented using data visualisation techniques. The second chapter highlights the pivotal role of industrial design as a key driver of exports. Furthermore, the empirical analysis establishes a correlation between industrial design and intellectual property protection in relation to exports. Recognising the growing importance of international design collaboration, the subsequent chapter explores the crucial role of air connectivity in facilitating such collaboration. Findings of this study suggest that industrial design is acknowledged as a significant driver of exports. Additionally, the intention to export also influences the registration of design patents in foreign markets. Moreover, air connectivity plays a vital role in facilitating international design collaboration.

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Chapter 1

Introduction

Industrial design refers to an integrated process of problem-solving ideas, craftsmanship, the appearance of outputs, and the production process. As an outcome of industrial design, design rights are considered as intellectual property (IP) rights to be legally protected. According to the World Intellectual Property Organization (WIPO) (WIPO, 16/01/2023), ”in a legal sense, an industrial design constitutes the ornamental aspect of an article. An industrial design may consist of three-dimensional features, such as the shape of an article, or two-dimensional features, such as patterns, lines, or color.” Obviously, the definition of industrial design varies in different contexts. In a general understanding, industrial design is considered as an idea that encompasses everything from conception to production and the resulting outputs. Regarded as an IP right, industrial design is measurable and evaluable.

In the market, aesthetics impact consumers' preferences and choices, and industrial design could lead to business success (WIPO, 2023f). For example, Apple's sleek and minimalist designs for its iPhones and MacBooks have significantly contributed to its brand image and market success (WIPO, 2012). Dyson's vacuum cleaners, featuring distinctive and futuristic designs, have established the company as a leader in the home appliance market (WIPO, 2012).

Compared to traditional patent rights, industrial design has a clear distinction. An industrial design right protects only the appearance or aesthetic features of a product, whereas a patent protects an invention that offers a new technical solution to a problem (WIPO, 2023a). While industrial designs and copyright can overlap, known as "cumulative protection," this occurs when industrial property and copyright intersect, allowing certain designs to be protected under both systems simultaneously. However, industrial design rights focus on the aesthetic features or appearance of a product, while copyright safeguards the underlying expression of an idea (Sharma and R, 02/05/2021). Industrial design rights emphasize visual aspects, whereas copyright extends to a broader range of creative expressions beyond visual appearance (WIPO, 2002).

Industrial design plays a crucial role as the catalyst in knowledge economy, it drives innovation, improves products from both the production and the user sides (Design

Council, 2011, 2017; Gemsera and Leendersb, 2001; Hertenstein et al., 2005). Integrating aesthetics, functionality, user experience, and the societal value, industrial design improves the ability of goods to meet the market preferences, and further lead the market demands (Bruce and Bessant, 2005; Montresor and Vezzani, 2017). On the other hand, the innovation capability is promoted by industrial design, therefore, the market competitiveness can be improved (Carlgren et al., 2014). In brief, industrial design contributes to the economic growth via its important impact on innovation and competitiveness of firms, regions or nations, and finally, its effects are significantly reflected on the global knowledge economy.

As it has been discussed, industrial design is often mentioned as the promoting role in innovation (Quaiser and Pandey, 2023), and its positive effects on knowledge economy tends to be discussed broaderly in existing research (Novoa, 2018). There is a lack of empirical research to investigate to what extent industrial design impacts economic indicators. Especially, exports is a key indicator when evaluating the success of a certain country in the Global Value Chains (GVCs) (OECD, 2007, 2017). Exports enable firms to specialize in specific stages of the value chain, taking advantage of their comparative advantages and reducing costs (Blancheton and Chhorn, 2019; Pio et al., 2021), these functions of exports are similar with the functions of industrial design. Therefore, export is a good place to start the investigation to the role of industrial design in knowledge economy.

This thesis attempts to explore the role of industrial design in the context of knowledge economy, the investigation is conducted in four stages, including the exploration of global patterns of industrial design registration with the aid of data visualisation; the examination of both the direct and indirect effects of industrial design on exports; the test of interdependencies between industrial design and exports by the PVAR approach; and the discovery of the role of air connectivity in facilitating international design collaboration. In conclusion, the finding of this thesis suggests a promoting role of industrial design in the knowledge economy, while its positive impact has been empirically evident from various perspectives in this study.

Chapter 1 is the introduction to the whole thesis from a comprehensive angle, the context of the whole research is discussed in the section 1.1. In Section 1.2, the data collected in this study is introduced, the utilisation of theses data into different chapters and corresponding measures computed are discussed. Next, Section 1.3 aims to summarise the methodology used in different chapters of this thesis. With different methodologies applied into different chapters, results would be highlighted and linked with existing research in the Section 1.4, this is a summary discussion for all results discovered in different single chapters. Finally, Section 1.5 concludes all findings of this thesis and summarise this introduction chapter in brief, while a comprehensive summary of all conclusions of this thesis is written in Chapter 6.

1.1 Context

Industrial design has undergone significant evolution since its beginnings in the early 20th century. Initially, designers like Peter Behrens focused on unified, utilitarian forms for mass production (Dormer, 1993). Streamlining and aerodynamic shapes gained popularity in the 1920s (Heskett, 1980). Post-World War II, ”Good Design” emphasized affordable, democratic products with honest materials and simplified forms (Sparke, 1983). In the 1960s, ergonomics and social concerns took center stage, considering how products shape human environments and behaviors (Heskett, 2006). Digital technology revolutionized design tools and global markets. Sustainable design emerged, acknowledging environmental impacts (Strauss and Fuad-Luke, 2008). Today, industrial design is diverse, covering electronics, medical equipment, furniture, transportation, and more (Lidwell et al., 2010). Styles range from minimalist to expressive, with a growing emphasis on interactive and user-centered design. Interdisciplinary approaches combining industrial design with engineering, marketing, and social sciences are common.

Along with the evolution of industrial design, its role is more and more important in contributing to economic growth. As industries become more knowledge-intensive, the value of products and services increasingly relies on their design and user experience. The evolution of industrial design has shifted its focus from mere aesthetics to a strategic approach that incorporates user-centered design, ergonomics, and sustainability (Borja-de-Mozota, 2003). By integrating these elements, industrial design enhances the functionality, usability, and desirability of products, ultimately leading to increased consumer adoption and market success.

Existing literature has sufficiently discussed the evolution of industrial design from the historical and theoretical perspectives, the gap is the exploration of the evolution of industrial design from the data perspective. Therefore, using the historical design registration records collected from Questel IP, with the aid of data visualisation, Chapter 1 fills this gap. This chapter discusses the evolution and the global patterns of design registration with various types of graphs.

In the knowledge economy, where innovation and creativity are key drivers, industrial design fosters the development of new and improved products that meet the evolving needs and desires of consumers (Tether et al., 2005). It encourages the generation of novel ideas, the exploration of alternative solutions, and the integration of cutting-edge technologies. Furthermore, industrial design facilitates the successful commercialization of innovations by bridging the gap between technological advancements and market demand (Borja-de-Mozota, 2003). By considering factors such as market trends, user preferences, and competitive landscapes, industrial designers contribute to the creation of products that are not only technologically advanced but also commercially viable.

It allows firms with high-quality industrial design can have a high competitiveness in the global market, while usually, the competitiveness of different countries are also reflected on their exporting performance (C. H. Kim, 1989). The role of exports in the global value chain is significant (Ahmed-Hannan et al., 2015; Banga, 2014). A good exporting performance of countries is often related with a high level of knowledge transformation efficiency and the technology utilisation productivity (Antonietti and Cainelli, 2011; Hatemi-J and Irandoust, 2001). This is where single firms can grow healthily and rapidly, and finally results in the sustainable growth of economies.

Although it can be seen a large body literature has explored the industrial design in the context of innovation, and the importance of innovation in exports, there is a lack of research which investigates the role of industrial design literately in exports. It does not mean industrial design must plays a direct promoting role in exports, it means that existing literature does not directly put industrial design into the exports context. Therefore, this study hopes to fill this gap.

Chapter 3 investigates the role of industrial design in exports from both direct and indirect perspectives. Which means that possibly industrial design have both the direct and moderating effects on exports. Employing the design data collected from Questel IP, and the exports data collected from UN Comtrade, various variables are constructed to explore the impact of industrial design in exports from different aspects. With the PPML estimation, and interaction term between different variables, industrial design's role in sufficiently examined in exports. In conclusion, this chapter has confirmed the promoting role of industrial design in exports empirically, while it has both the direct and indirect effects on exports.

Besides the positive effects from industrial design to exports, existing literature also mention that industrial design is often motivated by exporting intentions to a significant extent (WIPO, 2006). When businesses aim to expand their market reach beyond domestic borders, they recognize the importance of designing products that appeal to international consumers (Calantone, Kim et al., 2006). To successfully penetrate foreign markets, companies must consider factors such as aesthetics, functionality, usability, and local regulations (Calantone, Tamer-Cavusgil et al., 2004). Furthermore, as an intellectual property, industrial design which is protected overseas enables businesses to hold a comparative advantage in a foreign market (Belderbos, 2001; Zhang et al., 2022).

Take into account the impact of industrial design on exports has been tested to be true in Chapter 3, it is reasonable to speculate the interdependencies between overseas design registration and exports. Nonetheless, from existing literature, this point of view has not been investigated empirically. Thus, Chapter 4 contributes to empirical research from the perspective of exploring the interrelationships between industrial design and exports. In this chapter, using the same raw data used in previous analysis, and the exports data derived from UNTRADEINFO, variables are constructed to measure different aspects of overseas industrial design as well as the exports. With the aid of Panel Vector Autoregression, interdependencies of industrial design and exports have been examined as true.

In the 3 chapters which are mentioned above, it has been sufficiently discussed the motives for conducting corresponding topics in this thesis. The importance of industrial design in the context of knowledge economy has been highlighted, the global pattern and evolution of industrial design registration is been discussed, the promoting role of industrial design in exports has been investigated, the interdependencies between industrial design and exports are also examined. It has been clear that industrial design has a more and more important position along with the grow of knowledge economy under globalisation, till here, another important issue which may impact on both industrial design and the global knowledge economy is that cross-border collaboration (Arunachalam and Doss, 2000; Freshwater et al., 2006).

Cross-border collaboration is becoming increasingly important in today's interconnected world (Glinos, 2011). Cross-border collaboration allows countries, organizations, and individuals to pool their resources, expertise, and perspectives to tackle these complex issues more effectively (Espin et al., 2016; Romano et al., 2010). It promotes innovation and drives economic growth. By bringing together diverse talents, ideas, and resources from different countries, collaborations can lead to the development of groundbreaking technologies, products, and services. This exchange of knowledge and expertise can help the development of industrial design which is included in the broader concept of innovation (Qiu et al., 2022).

In the context of industrial design, cross-border collaboration is existing in the form of international design collaborations. Beside the importance of international collaboration which has been highlighted above, it deserves to investigate the facilitating factors of international design collaboration. Along with the development of artificial intelligence, online communication emerges as an integral part of people's life (Ryzhkova, 2015). However, in professional collaborations, for example, the collaboration in industrial designs, there is a doubt that whether or not face-to-face communication is crucial, or it can be replaced by online communication.

Existing literature have explored the role of face-to-face communication in scientific collaboration, which is irreplaceable (Asheim et al., 2007; Atkin et al., 2022). However, this is not specifically explored in the context of industrial design. In industrial design, there is a lack of literature to investigate the role of face-to-face communication in facilitating international collaboration. On the other hand, when talking about the face-to-face communication in case of international collaborations, air transport is regarded as the most effective tool for collaborators to meet each other in person (Brueckner, 2003). Therefore, to a extent, air connectivity which is measured by the intensity of air transport between different countries can represent the facilitating degrees of face-to-face communication between different countries.

Chapter 5 investigates to what extent air connectivity is facilitating international design collaboration, with the design data collected from Questel IP and the air transport data collected from OAG over the period 2013-2018. Employing the PPML (Poisson

Pseudo Maximum Likelihood) estimation, the impact of air connectivity on international design collaborations is examined as positive and significant, moreover, it can be found that air connectivity has a complementary effect with online communication instead of the substitution effect.

In summary, this research explores the role of industrial design in the knowledge economy and its contribution to economic growth. Industrial design is seen as a catalyst for innovation and improvement in products, integrating aesthetics, functionality, user experience, and societal value. By enhancing the ability of goods to meet market preferences and driving innovation, industrial design improves the competitiveness of firms, regions, and nations. The research focuses on the impact of industrial design on exports, considering it as an indicator of success in the global value chains. The study finds that industrial design plays a promoting role in exports and positively influences economic indicators. The research also examines the interdependencies between industrial design and exports, as well as the role of air connectivity in facilitating international design collaboration. Overall, the findings highlight the significant impact of industrial design on the knowledge economy and its role in driving innovation and competitiveness.

1.2 Data and Measures

The data employed in this study is collected from multiple sources in order to generate different variables according to the research purposes of different chapters. This section focuses on the introduction of data and measures of industrial design used in different chapters, because they are the key factors investigated in this study. Other data will be described in detail in each chapters.

The design data is collected from Questel IP, raw data is the design registration records with the information of the serial number of registration which is the ID for each single design as a patent. Also, it covers the description of industrial design to claim the objects, purpose, and what usage filed is designated for this design. By these information, with the aid of text mining, designs can be investigated from the perspective of their creation purpose and the application industries. Moreover, the raw data also covers the international standard classification for industrial design which is the Locarno classification. Therefore, designs can also be classified into different categories without analysing their detailed descriptions.

On the other hand, design owners and creators information is also covered in the raw data. By extracting their country codes from the address, ownership countries of designs are able to analysed. Moreover, when registering, if designs are registered via international IP offices, such as WIPO, ARIPO, EUIPO, and BXIPO, they are possibly to be designated to multiple protection territories which may not be same as the owner countries. This enables designs to be investigated from the perspective of cross-border registration.

The time information covered in the raw data include the application data, registration date, and the publication date of a registered design. In order to maximise the non-missing information, a new date column is generated according to all the available dates, using the union of all three different time information. The research in this study which involves time information of design registration is generated according to the newly generated date column in the raw dataset.

In order to generally explore the global pattern and evolution of industrial design registrations, based on the raw data, Chapter 2 calculates count of industrial design registrations for different purposes. At this stages, industrial design is measured using the simple count during certain time periods, or registered by different countries, or protected into different territories.

Moreover, in Chapter 3, design data is subset according to their protection territories during 1989-2018, 30 year in total. Variables are constructed in order to measure industrial design from different perspectives. Design capability is a variable which captures the innovation size of economies in terms of industrial design. According to the methodology proposed by Hidalgo, Klinger et al. (2007), the variables including design relatedness, design relatedness density, design complexity, design similarity, and design comparative advantage are constructed to test hypotheses proposed in this chapter.

Limiting raw data by the owner countries, designs which are owned by UK can be accessed. In depth, since the protection territories of industrial design are accessed, therefore, if the territory is different from the owner countries for the same design record, this term of industrial design is recorgnised as the overseas or cross-border registration. Selecting all designs which are owned by UK and registered outside the UK, Chapter 4 construct the variable of number of overseas design registrations, and the variable of design relatedness density in order to test the interdependencies between industrial design and exports. In this chapter, a quarterly panel is generated finally which is applied into PVAR model, the data covers 2013-2019.

Owner information is complicated in the raw data, which not only means that owners information includes both the name of owners and the detailed address of owners but also means that number of owners may be more than one for a certain industrial design. Nonetheless, this enables the collaboration of industrial design can be identified which is the foundation of data utilisation of Chapter 5. Here, number of international design collaborations is generated as the dependent variable to be explained by the air connectivity which is measured by air traffic data collected via OAG, the time period covered in this research is 2013-2018.

In summary, the data used in this study is collected from various sources to generate different variables for each chapter. The design data is obtained from Questel IP, consisting of registration records with serial numbers and descriptions of industrial designs. This information allows for analysis of design purposes and application industries through text mining. Additionally, the data includes the Locarno classification, enabling classification of designs into different categories. Ownership countries of designs are analyzed by extracting country codes from addresses, and cross-border registrations are examined when designs are registered via international IP offices. The time information in the data includes application, registration, and publication dates, and a new date column is generated to maximize data availability. Chapter 2 explores the global pattern and evolution of industrial design registrations, while Chapter 3 focuses on design data subset by protection territories and constructs variables to measure design capability from various perspectives. Chapter 4 investigates interdependencies between industrial design and exports by selecting designs owned by the UK and registered outside the country. Chapter 5 examines international design collaborations by identifying collaborations through complex owner information and explores their relationship with air connectivity measured by air traffic data.

1.3 Methodology

The methodologies employed in this study varies according to different research purposes of chapters, this study as a whole is a quantitative research, therefore, all single methodologies in each chapters are quantitative. In order to present an overview of industrial design data, Chapter 2 involves the methods of data visualisation to present statistics of industrial design data. Chapter 3 aims to explore the impact of industrial design on exports, here, export is the dependent variable, therefore, the structural gravity model is employed and estimated via PPML in this research. Moreover, to investigate the interrelationship between industrial design and exports, Chapter 4 utilise the Panel Vector Autoregression as the estimation methods. Furthermore, employing the number of international design collaborations as the dependent variable, Chapter 5 examines the role of air connectivity in facilitating international design collaboration via PPML estimation. In brief, this study employs the quantitative methods to investigate specific research questions each single chapters, estimation methods vary according to requirements of both data and theories of different chapters.

1.4 Results and Discussion

The main findings of this thesis suggest that industrial design plays an important role in knowledge economy. This point is discussed in this thesis from the perspective of the promoting role of industrial design in exports, furthermore, the relationship between industrial design and exports is not single-way, which means that exports can reversely affect design registrations. Besides, as the increasing importance of international collaboration in the context of globalisation, the cross-border owned designs are increasing along time. Air connectivity is considered to play a significant role in international design collaboration. The next content of this section would introduce and discuss the findings of each chapter in brief.

Chapter 2 utilizes data visualization to explore the evolution of global industrial design, highlighting its connection to industry revolutions and the influence of owner countries and target markets. The study reveals the unique distribution of industrial design across different Locarno classes, with high-tech products playing a central role. The findings emphasize the significant impact of technological advancements, consumer demands, and global connectivity on the development of industrial design. Additionally, the research identifies the drivers of industrial design, including technologies, ownership countries, and target markets. The study also highlights the importance of cross-border design registrations and the role of the European market in global industrial design. Overall, this research contributes to a comprehensive understanding of industrial design from multiple perspectives, shedding light on its evolution and significance in the global economy.

Chapter 3 explores the impact of design on exports, specifically investigating the effects of design capability, design comparative advantage, design relatedness, design similarity, and design complexity. The findings highlight the positive influence of design capability, design comparative advantage, and design relatedness on exports. Additionally, the study reveals the negative impact of design similarity on exports, while design complexity mediates the relationship between design comparative advantage and exports, as well as the relationship between export structure similarity and exports. This research contributes to the literature by providing empirical evidence on the promoting effect of design on exports at the national level. It introduces new variables, such as design comparative advantage, design relatedness, design similarity, and design complexity, to capture different aspects of design innovation and their impact on exports. The findings of this study can inform policymakers and firms on the importance of design innovation in promoting exports and enhancing competitiveness in the global market.

Chapter 4 investigates the interdependencies among overseas design relatedness, overseas design registration, and exports. The findings reveal the mutual causality among these variables and highlight their significant role in promoting each other. The study also identifies the drivers of overseas design registration, design relatedness, and exports. The results demonstrate the influence of design relatedness and exports on the number of design registrations, with design relatedness having a larger effect. Additionally, the number of design registrations and design relatedness significantly drive exports, with design relatedness being the more influential factor. The study contributes to the literature by providing empirical evidence on the interdependencies and drivers of overseas design relatedness, design registration, and exports. These findings can inform policymakers and businesses on the importance of fostering design-related activities and knowledge networks to enhance international trade and economic growth.

Chapter 5 provides empirical evidence of the positive effect of air connectivity on international design collaboration. The findings demonstrate that air connectivity has a significant impact on promoting collaboration, especially in sectors that rely heavily on face-to-face communication. The study also highlights the complementary effect of air connectivity and virtual connectivity, with air connectivity playing a more important role in countries with a higher level of online social connectedness. Although, there are limitations in accurately measuring air connectivity at a sectoral level and capturing the changing demand for face-to-face communication over time, this research contributes to the understanding of the factors that facilitate international design collaboration and provides insights into the importance of physical and virtual connectivity in knowledge exchange. Overall, this research sheds light on the role of air connectivity in driving international design collaboration and suggests strategies to enhance collaboration in the field.

In brief, the main findings of this thesis highlight the significant role of industrial design in the knowledge economy. The research explores the relationship between industrial design and exports, revealing that exports can have a reverse effect on design registrations. The study also emphasizes the increasing importance of international collaboration in design, with cross-border owned designs on the rise. Additionally, the research demonstrates the positive impact of air connectivity on international design collaboration, particularly in sectors that rely on face-to-face communication. The findings contribute to a comprehensive understanding of industrial design, its drivers, and its impact on exports and to what extent its international collaboration can be promoted.

1.5 Summary

The introduction chapter provides an overview of the research conducted in this thesis on the role of industrial design in the knowledge economy. It highlights the importance of industrial design in driving innovation and improving products, leading to economic growth. The chapter identifies the gap in empirical research on the impact of industrial design on economic indicators, particularly exports. It argues that exports are a good indicator to investigate the role of industrial design in the knowledge economy, as both exports and industrial design contribute to the competitiveness of firms and nations.

Four stages of the research conducted in this thesis are outlined in this chapter. First, the exploration of global patterns of industrial design registration using data visualization. Second, the examination of the direct and indirect effects of industrial design on exports. Third, the investigation of the interdependencies between industrial design and exports using the Panel Vector Autoregression (PVAR) approach. And finally, the exploration of the role of air connectivity in facilitating international design collaboration.

The data section of the chapter introduces the data and measures used in the study. The design data is collected from Questel IP and includes registration records with information on industrial design descriptions, ownership countries, protection territories, and time information. The data is used to explore the global patterns and evolution of industrial design registrations, as well as to construct variables for measuring design capability, design relatedness, and overseas design registration. The chapter also mentions the use of exports data from UN Comtrade and air transport data from OAG in specific chapters. Overall, the data section provides an overview of the data sources and variables used in the study.

The methodology section provides an overview of the quantitative methods employed in the study. It mentions the use of data visualization in Chapter 2 to explore the global patterns and evolution of industrial design registrations. Chapter 3 employs the structural gravity model and estimates it through the Poisson Pseudo Maximum Likelihood (PPML) method to explore the impact of industrial design on exports. Chapter 4 utilizes the Panel Vector Autoregression (PVAR) approach to examine the interdependencies between industrial design and exports. Chapter 5 employs the PPML estimation to investigate the role of air connectivity in facilitating international design collaboration.

The chapter concludes by summarizing the findings of the thesis, which suggest a promoting role of industrial design in the knowledge economy. It highlights the empirical evidence of industrial design's positive impact on exports and the interdependencies between industrial design and exports. It also emphasizes the significant role of air connectivity in facilitating international design collaboration.

In summary, the introduction chapter provides a comprehensive overview of the research conducted in this thesis and sets the stage for the subsequent chapters. It highlights the importance of industrial design in the knowledge economy and outlines the research objectives and methodology. The chapter also introduces the data used in the study and provides an overview of the variables constructed for each chapter.

Chapter 2

Context of Industrial Design

2.1 Introduction

Industrial design plays a crucial role in shaping the global economy, driving innovation, and enhancing competitiveness across industries (Arab News, 2022). Its evolution is closely tied to industry revolutions and technological advancements (Huang and Jia, 2022). Understanding the development, characteristics, and global interconnectedness of industrial design is essential for policymakers, businesses, and researchers seeking to navigate this dynamic field. This paper aims to provide a comprehensive analysis of the evolution, characteristics, and global interconnectedness of industrial design, shedding light on its significance in the modern marketplace.

The evolution of industrial design can be traced back to the early stages of industrialisation, where the emergence of new manufacturing processes and mass production transformed industries (Borja-de-Mozota, 2008; Heskett, 1980). Over time, industry revolutions, such as the advent of electricity, automation, and digital technologies, have further propelled the development of industrial design (Hatchuel and Weil, 2003; Vinsel, 2020). These revolutions have not only revolutionised manufacturing processes but have also shaped consumer demands and market dynamics (Hatchuel and Weil, 2009; Raizman, 2003). As a result, industrial design has evolved to meet the changing needs of consumers and adapt to the technological advancements of each era (Crilly et al., 2004).

There has been sufficient literature explaining the evolution and global landscape of industrial design. However, there is a lack of empirical perspective that explores the evolution and global distribution of industrial design using historical data of design registrations. By combining existing literature with empirical analysis based on historical data of industrial design, a comprehensive understanding of industrial design and its role in the context of the knowledge economy can be obtained.

To gain a deeper understanding of industrial design, this chapter incorporates a review of existing literature. The background section reveals key concepts and theories related to industrial design, providing insights into its definition, historical context, and its role in innovation and economic development (Bruce and Bessant, 2002; Hertenstein et al., 2005). It explores scholarly research to uncover the characteristics and trends shaping the field of industrial design.

Additionally, this chapter utilises data visualisation techniques to present and analyse patterns in the distribution and characteristics of industrial design. By visualising data, valuable insights into the global interconnectedness of industrial design are obtained, exploring the concentration of design registrations in specific countries and markets, as well as illustrating the prevalence of cross-border design registrations through various types of graphs.

The use of data visualisation to explore global industrial design reveals its evolution and distinctive distribution across different Locarno classes. Industrial design is heavily influenced by industry revolutions, technological advancements, changing consumer demands, and evolving societal values. The drivers of industrial design are identified as technologies, ownership countries, and target markets, with technological advancements being a core driver. Industrial design is significantly influenced by economies as design owner countries and target markets, with cross-border design registrations indicating the importance of protecting intellectual property and gaining a competitive advantage in foreign markets. The European market emerges as a significant hub for industrial design, necessitating businesses expanding into the global market to consider it as a key target for their industrial design strategies.

2.2 Background

The field of industrial design can be approached from three perspectives. Firstly, it can be seen as a form of extensive innovation in businesses (Verganti, 2009), where design activities are applied to mass production and the creation of physical goods (Crilly et al., 2004). Secondly, from a legal standpoint, industrial design refers to the registration of design patents through official Intellectual Property Offices (IPOs) worldwide, providing protection against unauthorised commercial activities (Hertenstein et al., 2005). Lastly, registered industrial design is considered an intangible asset for businesses (Deichmann et al., 2020).

2.2.1 Concepts of Industrial Design

According to the literature which mentions the evolution and history of industrial design (Buchanan, 1992; Fallan, 2010; Heskett, 2005; Margolin and Buchanan, 1995; Pevsner, 1975), the definition of design can be traced back to 1588, where it was described as a scheme, plan, graphic draft, or object of art. However, the concept of design has evolved over time. Notably, Leonardo da Vinci and Giorgio Vasari were early proponents of design, recognising its role in bridge construction and artistic expression, respectively. Design was initially seen as an incomplete work, with drawings and sketches serving as part of the creative process. The term *industrial design* was first defined by Mart Stam in 1948 as a draft, sketch, or plan employed in every phase of industry. While there are no fundamental differences between the early definition of design and industrial design, the latter specifically highlights its application in the industrial sector. In the second half of the 20th century, design became a more complex concept (Simon, 1988), encompassing not only individuality expressed through products but also facilitating user experiences and enhancing the connection between technology and finished products.

Contemporary design combines elements of traditional arts and industrial applications, emphasising both craftsmanship and mass production (Homburg et al., 2015; Ünsal, 2018). Design plays a role in various stages of the global value chain, including manufacturing and marketing. In manufacturing, industrial design involves design thinking, which focuses on mass production planning and solutions to potential manufacturing issues. Consideration of market preferences, customer needs, and resource allocation are also essential. In the marketing stage, design, particularly for advertising purposes, overlaps with traditional art. Thus, modern industrial design is a comprehensive concept that supports business development while being influenced by business factors (Borja-de-Mozota, 2008; Hertenstein et al., 2005).

2.2.2 Design in Industries and the Knowledge Economy

The concept of the knowledge economy has expanded beyond its original definition which solely focused on the production of new technologies (Castells, 2009; Fagerberg, 2009; Foray, 2006; Lundvall, 2007; Mokyr, 2005). It now encompasses social and informational dimensions, recognising the intertwined relationship between knowledge and economic growth (Dosi, 1988; Florida, 1995; Neef et al., 2011; Pavitt, 1995; Stiglitz, 1999). In the knowledge economy, the impact of time and distance on economic growth is reduced (Cairncross, 1998; Glaeser, Kolko and Saiz, 2001; Graham, 2002; Naylor and Florida, 2003; Saxenian, 1996). Knowledge, acquired through experience, training, learning, and familiarity, plays a crucial role in driving innovation in commercial activities (Davenport and Prusak, 1998; Foss and Klein, 2012; Grant, 1996; Nonaka, 1996; Teece, 1998). It enhances productivity and competitiveness by improving capabilities and creativity (Bresnahan et al., 2002; Brynjolfsson and McAfee, 2016; Hitt and Brynjolfsson, 1996). Well-educated labour capable of collecting and absorbing information reduces search costs and increases firms' competitiveness (Acemoglu and Pischke, 2001; Krueger and Lindahl, 2001; Mincer, 1974). Moreover, the aggregation of knowledge not only provides a skilled workforce but also creates a consumer market with high demand, as demonstrated by the creative class (Raspe and Van-Oort, 2006). Design, as a form of innovation, is inherently involved in the knowledge-based economy (T. Brown and Katz, 2011; Heskett, 2005).

Knowledge is built upon information extracted from data and is closely related to cognitive skills (Davenport and Prusak, 1998; Grant, 1996; Nonaka, 1996; Spender, 1996). A nation's knowledge assets, which are intangible assets, contribute to national growth and value creation for stakeholders (Corrado, Haskel and Jona-Lasinio, 2017; Haskel and Westlake, 2018). The transition from energy-based economies to information-based economies involves intellectual capital, which comprises intangible or knowledge assets (Barão et al., 2017; Edvinsson and Malone, 1997). These assets include technologies, competences, and capabilities, which can be categorised as structural capital (software systems, distribution networks, and supply chains) and human capital (related to employees and customers) (Edvinsson and Malone, 1997).

National knowledge-based capital encompasses the development of society, culture, and human capital (Tomé, 2011). In an economy, knowledge is linked to marginal productivity and plays a significant role in explaining long-term growth (Jones, 2002). Evidence supports the idea that countries with high-quality patents experience higher economic growth (Griliches, 1998). Furthermore, countries that take actions to improve patent behaviour also witness improvements in economic growth (Hasan and Tucci, 2010; Malhotra, 2003).

In regional economies, knowledge spillovers are influenced by labour skills and research and development (R&D) intensity (Radwan and Pellegrini, 2010; Stejskal et al., 2018). Unlike information sharing, geographic proximity alone does not have a significant impact on knowledge spillovers; instead, they often result from high firm density (Glaeser and Kerr, 2009). Human capital and patent citations act as channels for knowledge spillovers, enhancing labour productivity and capital sharing (Acemoglu and Pischke, 2001). A high degree of human capital, along with high-skill labour, scientists, and engineers, improves knowledge capital and firm productivity (Cohen and Morrison Paul, 2008).

Knowledge capital, also known as intangible assets in corporations, includes elements such as brands and trademarks. The value of intangible capital increases over time (Malhotra, 2000). According to Davenport and Prusak (1998), knowledge capital encompasses the commercial relationships between corporations, clients, and employees' knowledge and abilities, including financial elements that measure a company's success (Malhotra, 2000). It is evident that firm growth is positively related to national growth. For example, Israel experienced rapid economic growth since 1950, accompanied by the growth of numerous high-tech companies (Malhotra, 2000).

Oslo Manual 2018 (OECD, 2018), published by the OECD, discusses design as a form of innovation. The OECD's perspective on design aligns with that of Design Council (2018), recognising design as both a resource and a form of innovation. While design activities may not meet all criteria for research and development (R&D), they are significantly relevant to R&D. In particular, *reverse engineering* involves extracting knowledge from existing products or equipment to develop functions or improve appearance, shortening the gap between users and technology and enhancing user experience (Hernández et al., 2018). Design, when combined with other creative activities, supports firm innovation (OECD, 2018). Comparing the current and previous editions of the Oslo Manual, the 2005 version did not include the role of design in product innovation (OECD, 2005), while the 2018 edition addressed design's position in both production and marketing innovation. The emphasis on design has been increasing over time (OECD, 2018). Design capabilities can be categorised into engineering design, product design, and design thinking (OECD, 2018).

Design Council (2018) classifies design activities based on the occupations involved in design creation work. At the same time, with reference to other relevant literature (Gann and Salter, 2000; Hertenstein et al., 2005; Norman, 2013; Saki et al., 2019), the types of design can be divided into product and industrial designs (e.g., furniture design in wood product manufacturing, electrical equipment design in consumer electronics manufacturing), graphic and clothing designs (e.g., fashion designs, dressmaking, accessory design), multidisciplinary designs (e.g., fashion, industrial, and sustainable designs), designs of architecture and the built environment (e.g., building, drafting, ecological designs), digital designs (e.g., software publishing, computer game development, computer programming activities), and advertising designs.

2.2.3 Industrial Design as Intellectual Property

Intellectual Property (IP) refers to the legal rights granted to individuals or organisations for their creations or inventions (Mingaleva and Mirskikh, 2013). It encompasses various types of protection that offer legal safeguards from different perspectives (Ruse-Khan, 2016). Patents and utility models protect the functional aspects of products, while industrial designs safeguard the aesthetics and appearance of articles (Carroll, 2009). Copyrights protect complete artistic, literary, or cultural works, while trademarks, geographical indications, certification marks, and collective marks protect unique signs (D. Yang and Clarke, 2005). Trade secrets safeguard commercial secrets such as clients, working procedures, and strategies (Aplin, 2014). Additionally, trade names protect the unique names of businesses. IP owners obtain legal protection for their inventions or creations by filing applications with IP offices worldwide (Jaiya, 2016).

Industrial design, also known as a design patent, differs from a traditional patent in that it focuses on protecting the appearance of products rather than their functionality (IPWatchdog, 2022; A. J. Park, 2023; Ulrich, 2012). Registering industrial designs is often more convenient for applicants, particularly for businesses whose sales heavily rely on the aesthetic appeal of their products (Europe Economics, 2015). According to WIPO (2023c) and GOV.UK (9/1/2023), the application process for industrial design is typically faster, with IP rights granted within 12 months, whereas patent applications usually require two to three years for examination. Once the design is registered as a design patent, the graphics, lines, colours, and raw materials of the object are protected for a duration of at least 10 years and a maximum of 25 years. The protection can be renewed every five years. Industrial design protection has limitations, as it solely safeguards the visual aspects of products. If other products incorporate the same underlying ideas but have different appearances, it would not be considered infringement. Additionally, if an industrial design incorporates components that are already protected by copyright, it may infringe on the copyright holder's rights (WTM, 2023; J. Yang, 2012).

Currently, there is no concept of *international industrial design rights* as design rights are exclusively territorial and granted and protected within the jurisdiction of the registration country. When an individual registers a design with an international intellectual property office, such as WIPO, EUIPO, BXIPO, or ARIPO, it is necessary to designate at least one signatory party of the respective intellectual property organisation as the protection country (WIPO, 2023c). Given the territorial nature of industrial design rights, their characteristics and provisions differ across countries. The specific requirements pertaining to subject matter, duration, application, publication, and examination are contingent upon the regulations of the registration country (WIPO, 2023c). Consequently, registered design rights exhibit distinctive features in various countries. To illustrate the national disparities, this discussion will focus on several countries and regions as examples, including Canada, China, France, Germany, Italy, Japan, South Korea, the United Kingdom, the United States, and the European Union.

These countries employ different naming conventions for their national registered design rights. In Canada, it is referred to as *Industrial Design*, which aligns with the terminology used by WIPO (Citaristi, 2022; McMaster, 1998). China and the United States use the term *Design Patent*, while France and Italy include the term 'Models' in their respective design rights, known as *Designs and Models* in France and *Design and*

Model in Italy (Gallié and Legros, 2012; Moradei, 2009; Sorell, 2002; Xie and Zhang, 2015). Germany, Japan, and South Korea simply use the term *Designs* in Germany, and *Design* in Japan and South Korea (Blind et al., 2006; Maskus and McDaniel, 1999; J.-H. Park, 2009). In the United Kingdom and the European Union, the emphasis is placed on the *registered* aspect, resulting in the terms *Registered Design* in the UK and *Registered Community Design* in the EU (Graneris, 2019; Helmers and McDonagh, 2013). This distinction is made because unregistered industrial designs in the UK and EU are also protected as design rights.

Different countries have varying definitions of design. Canada and China do not protect partial segments of a design, while other countries include partial segments within their design definitions (Nikzad, 2013; Sorell, 2002). All the sample countries provide protection for the entire design. France, the UK, and the EU include design methods within their definitions, while other countries do not offer protection for design methods (R. S. Brown, 1986; Hudson, 1948). Symbolic or graphic elements of design are protected in all the sample countries except China. China, uniquely, considers the design as a whole and does not provide protection for partial segments, methods, symbols, or graphics (Dang and Motohashi, 2015). Conversely, the other sample countries offer partial protection to varying extents. France, the UK, and the EU provide comprehensive protection for partial segments, the entire design, methods, symbols, and graphics, while other countries offer limited protection (Lerner, 2002; Schickl, 2013).

The term of protection varies among countries. In Canada and the US, protection begins only after the design rights have been granted, while in other countries, protection commences upon filing the application (Fink and Maskus, 2005; Landes and Posner, 2003). The duration of protection also differs, with the maximum term ranging from 10 to 25 years, depending on the country (WIPO, 2023c). Additionally, differences exist in the examination process. Canada, China, Japan, South Korea, the UK, and the US require substantive examinations for registered design rights, whereas the remaining sample countries do not necessitate this step (OECD, 2005, 2018). Other distinctions, such as participation in international treaties and the application or registration process, are discussed in detail by WIPO (2023b).

In summary, industrial design rights vary significantly among different registration countries due to their territorial nature. However, many designs are registered with international IP offices to obtain cross-country protection (*Text - S.3486 - 112th Congress (2011-2012): Patent Law Treaties Implementation Act of 2012*, 2012). International treaties have attempted to standardise the protection territory and the cross-border registration of industrial design. The Berne Convention, established in 1886, is the first significant international treaty for copyrights (Goldstein and Hugenholtz, 2021). Although it does not specifically regulate design rights, it recognises design rights as a form of artistic work and provides protection under copyright law (Brean, 2008). The Paris Convention, signed in 1883 and last revised in 1967, is the first international patent treaty aimed at reducing trade barriers (Bellido, 2016; WIPO, 2023e). Industrial design is considered as an industrial property, consequently, along with globalisation, industrial design is often registered in an overseas market to have commercial businesses in a foreign market (WIPO and Manzano, 2018).

In 1994, the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) by the World Trade Organization (WTO) came into effect (Abbott, 2022; EUR-Lex, 1994; WTO, 1993). Although it does not provide a specific definition for industrial design, it integrates industrial design into the broader realm of intellectual property protection. The Hague Agreement Concerning the International Deposit of Industrial Designs, administered by the World Intellectual Property Organization (WIPO) (WIPO, 2023d), serves as a specialised agreement for the protection of industrial designs as design rights. This agreement offers international protection and outlines the duration of protection for registered design rights. Applications for protection are filed with the International Bureau of WIPO, ensuring that the design rights are protected in designated signatory parties (Galindo-Rueda and Millot, 2015; OECD, 2018; Weinstein, 2002-2003).

2.2.4 Motives of Patenting Industrial Design

The motives behind patenting industrial designs can be explored from the perspective of design owners. Design creators may not necessarily become the holders of corresponding design rights, while holding design rights incurs costs (X. Sun et al., 2021). Therefore, understanding the motives for design registration requires considering the position of design owners (Filippetti and D'Ippolito, 2017). According to Heikkilä and Peltoniemi (2019), typical motives for filing design applications include preventing piracy, generating revenue from licensing patents, avoiding litigation, blocking others' commercial use, negotiating from a position of strength, attracting capital investments, government incentives, and enhancing reputation to attract stakeholders. Firstly, the fundamental driver for applying for an IP right is protecting and encouraging creators, which applies to design rights as well (Blind et al., 2006; Giuri et al., 2007). In the fashion industry, piracy is particularly damaging, making effective legal protection for designs crucial (Raustiala and Sprigman, 2006; Terakura, 2000).

Secondly, patent monetisation is a primary motive for small and medium-sized enterprises (SMEs) to hold patents. Industrial designs can also be licensed, offering a sustainable source of revenue for design holders. Patent holders have a favourable position in licensing contracts, allowing them to determine the allocation of profits (Shapiro, 1985). This alleviates the financial difficulties faced by SMEs and attracts profit-driven investments in innovation, fostering a healthy capital chain and sustainable innovation (de Rassenfosse, 2012).

Thirdly, holding design patents provides firms with operational freedom resulting from innovation outputs. Innovation in firms is driven by profit-oriented motives, and patents provide the freedom to operate and gain a preemptive advantage in technologies (Guellec et al., 2012; Heikkilä and Peltoniemi, 2019). The operational rights granted by patents enable firms to control commercial activities involving relevant inventions or creations. Consequently, some companies may merge or acquire other companies holding patents (Grimpe and Hussinger, 2014; Ziedonis, 2004). Industrial design shares this characteristic with traditional patents, motivating firms to register designs to enjoy the freedom to operate.

Fourthly, industrial design protection prevents unauthorised commercial use by others. Piracy is often driven by commercial motives, and patent holders seek to safeguard their IP rights for commercial purposes. In addition to litigation against piracy, patentees aim to establish a monopoly in specific fields where they hold patents. Monopolists intend to maintain their market dominance through patenting (Gilbert and Newbery, 1982). Furthermore, patentees may retain unused patents to prevent potential competitors from entering the market (Torrisi et al., 2016). Lastly, holding design patents strengthens the negotiating position of design owners. In early years, even when patent rights did not have the same legal environment as today, patenting enabled owners to negotiate from a position of strength (Harabi, 1995). Holding patents can facilitate cooperation, entry into capital markets, and potential business opportunities (Blind et al., 2006).

2.3 Data

The data for this study on industrial design was obtained from Questel IP, a leading provider of intellectual property (IP) solutions and services. Their platform, Orbit, offers a user-friendly interface for searching and retrieving patent data, including records of industrial designs. The dataset comprises 16,341,918 records from 60 countries and 4 multinational intellectual property organisations, covering data up until 31/01/2020. It includes information such as registration details, owner information, application and registration dates, and more. This comprehensive collection of historical design records allows for further statistical analysis of industrial design trends and patterns.

2.3.1 Data Source and Data Collection

The data utilised for this study on industrial design is obtained from Questel IP, a prominent provider of intellectual property (IP) solutions and services. Questel IP offers a comprehensive platform enabling users to search and access patent data, including information related to industrial designs. It provides tools and databases assisting researchers, inventors, and IP professionals in analysing, protecting, and managing their intellectual property assets. The platform encompasses a wide range of features, including advanced search capabilities, data visualisation tools, legal status tracking, and portfolio management functionalities.

To collect the data for this study, the Orbit search engine platform developed by

Questel IP was employed. Orbit is specifically designed to offer users a user-friendly interface for searching and retrieving patent data, including records of industrial designs. It leverages the data and services provided by Questel IP to provide comprehensive and reliable information on patents. Orbit contains registered intellectual properties in various languages and formats, while standardising these patent documents into a readable and understandable format. This database ensures the retention of original information, such as different application numbering methods used by different IP offices and non-English expressions in application documents. The standardised format preserves all this information in the design rights records (WIPO, 2010).

When conducting a search for design data, the Orbit search interface provides advanced search capabilities. Users can specify certain fields to collect data, including designated date, designated countries, specific application numbers or registration numbers, and other relevant fields. For this study, all records of design data in the Orbit database were aimed to be obtained, and thus, no specific conditions were set during the search process. Additionally, to gather as much data as possible from all countries, all country options were selected in the advanced search interface.

2.3.2 Data Coverage

The data collection process resulted in a total of 8,222 XLS files, which were subsequently consolidated into a single CSV file containing 16,341,918 records. These records encompass information from 60 countries and 4 multinational intellectual property organisations. The dataset covers data up until 31/01/2020.

The data collection by Questel IP includes information from IP offices in 60 countries and 4 multinational intellectual property organisations. The countries included in the dataset are Albania (AL), Argentina (AR), Austria (AT), Bosnia and Herzegovina (BA), Bulgaria (BG), Brunei Darussalam (BN), Brazil (BR), Canada (CA), Switzerland (CH), China (CN), Colombia (CO), Cyprus (CY), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), United Kingdom (GB), Georgia (GE), Greece (GR), Croatia (HR), Hungary (HU), Indonesia (ID), Ireland (IE), India (IN), Iceland (IS), Italy (IT), Japan (JP), Cambodia (KH), Korea (KR), Lao People's Democratic Republic (LA), Lithuania (LT), Latvia (LV), Morocco (MA), Moldova (MD), North Macedonia (MK), Malta (MT), Mexico (MX), Malaysia (MY), Norway (NO), Peru (PE), Philippines (PH), Poland (PL), Portugal (PT), Romania (RO), Serbia (RS), Russia (RU), Sweden (SE), Singapore (SG), Slovenia (SI), Slovakia (SK), San Marino (SM), Thailand (TH), Tunisia (TN), Turkey (TR), United States (US), and Vietnam (VN).

The 4 multinational intellectual property organisations included in the dataset are the African Regional Intellectual Property Organisation (ARIPO) (AP), Benelux Office for Intellectual Property (BOIP) (BX), European Union Intellectual Property Office (EUIPO) (EU), and World Intellectual Property Organisation (WIPO) (WO).

The raw dataset comprises 55 variables and 16,341,918 observations. These variables encompass information such as the serial number of registration, country code, designation in English, original title, Locarno class, name and address of the owner, creator details, application number and date, registration and publication dates, description, number of industrial designs, legal status, priority details, agent information, expiration date of renewal, language of filing, designation in French, duration of protection, national class, main class, subclass, designated countries, and various other relevant fields. Thus, the observations in the dataset represent historical design records, and further statistical analysis needs to be conducted. The country code column in the dataset represents the country codes of IP offices, and the owner countries and designated protection territories need to be extracted from the variables of owner address and the designated countries, respectively.

2.4 Methodology

This chapter aims to explore the potential information in the industrial design data with the methods of data visualisation. Multiple types of charts are employed to illustrate different patterns in the data. This section will introduce the plotting methods of different types of charts as well as their application in the industrial design data.

2.4.1 Charts Involved in Data Visualisation

This section introduces several charts utilised in this chapter, such as the area chart, bar chart, bump chart, combo chart, polygonal geographic map, heatmap, line chart, marginal distribution chart, network chart, pie chart, radar chart, and scatter chart. These charts are valuable tools for visualising and analysing data in the context of industrial design, allowing for the exploration of trends, patterns, and relationships from various perspectives.

2.4.1.1 Area Chart

An area chart is a line chart with filled colours between the lines and the x-axis. It presents the area, which indicates the total value represented on the y-axis during a segment of values on the x-axis. By filling different colours to different lines and voids formed by the lines, it can be determined which colour or line has the largest area. This allows for the visualisation of the total amount of y-axis values for different categories of data on a certain segment of x-axis values. Additionally, the lines fluctuate along with the increase of values on the x-axis, allowing for the illustration of the trend of different data along with values on the x-axis.

2.4.1.2 Bar Chart

A bar chart presents each set of two values by the shape of a rectangular bar on a plane consisting of both an x-axis and a y-axis. Each set of two values, corresponding to the vertical and horizontal axes respectively, can be plotted on the plane as a point. Connecting the point to the corresponding value on any axis generates a straight line segment. Extending the line segment to the line chart creates the bar, with the length of the line segment representing the height of the bar.

Sometimes, the bar chart involves more than two dimensions. In this case, the stacked bar chart or the grouped bar chart are widely used to include more data dimensions. The stacked bar chart utilises different colours for stacked bars to represent different dimensions, while the grouped bar chart uses different groups to represent different dimensions. If the focus of the study is the comparison of the amounts of different axis categories, the stacked bar chart is used. If the focus is the comparison of different groups within each axis category, the grouped bar chart can be used.

2.4.1.3 Bump Chart

In contrast to line charts or bar charts that focus on the values of different entities, a bump chart focuses on the rankings of different entities. It consists of both x and y axes, with the y-axis representing the rankings of entities corresponding to the categories or values on the x-axis. This allows for the visualisation of the fluctuations in rankings of different entities over different time periods or categories presented on the x-axis.

2.4.1.4 Combo Chart

A combo chart, also known as a combination chart, refers to a chart that combines multiple x or y axes, each assigned different ranges of values or categories. The term *combo* emphasises the combination of different x or y axes with different value ranges, rather than the combination of different types of charts. Charts that use different shapes to present data but share the same x and y axes do not meet the definition of a combo chart in this study.

A combo chart allows for the exploration of the relationship between two different variables, enabling the visualisation of trends for multiple variables in the same chart. The choice of chart type depends on the characteristics of the data, although a commonly used type is the combination of bar and line charts.

2.4.1.5 Polygonal Geographic Map

The polygonal geographic map is a geographic map where land areas or regions are divided into discrete polygons using straight lines instead of traditional curved lines. Polygons are used to represent different data information, such as population, GDP, or land use. Different colours can be filled into the polygons based on the values or categories of the data, representing a range of values. This allows for the shading of different regions of the world with colours to represent their different levels for a variable. This enables easy visualisation and analysis of spatial patterns and relationships.

2.4.1.6 Heatmap

A heatmap is a two-dimensional matrix with shaded cells according to the corresponding values of elements. It enables the additional dimension, which is illustrated in colours, in addition to the two dimensions represented by the columns and rows of the matrix. It is often used to visualise the correlation relationship between variables on the columns and rows of the matrix. Furthermore, it is also an effective tool to present the value distribution of different categories presented on the columns and rows of the matrix respectively. Thus, it enables both the density and the trend of data to be visualised on the same chart.

2.4.1.7 Line Chart

A line chart is a type of graph used to present the trend of a set of values corresponding to another set of values. The layer of the line chart is a plane consisting of the x and y axes, with each set of values corresponding to the x-axis and y-axis presented as a point located on the plane. A line graph is obtained by connecting these points in sequence.

2.4.1.8 Marginal Distribution Chart

In a marginal distribution chart, two variables can be plotted on a basic two-dimensional chart which are presented respectively by the x and y axes. Usually, scatter or heatmap cells are used to represent different observations or the number of observations in the data. These observations are plotted onto the plane based on their x-values and y-values.

Additionally, since the two variables represented by the x and y axes have different density distributions, the density is shown on the margins of the basic plot.

A marginal distribution chart enables the relationship between two different variables to be displayed on the fundamental chart. At the same time, the density distribution of each variable can be displayed on the same chart. This is an effective way to understand and visualise both the summary statistics and the correlation relationship of different variables.

2.4.1.9 Network Chart

A network chart, also referred to as a network diagram or graph, serves as a visual depiction of interconnected nodes or entities. It visually represents the relationships and connections between these nodes through the use of lines or edges. Network charts find extensive application in various fields, including computer science, social sciences, and business, enabling the analysis and visualisation of intricate systems, networks, or relationships. They facilitate the identification of patterns, dependencies, and interactions among different elements within a network.

In this chapter, a network chart is employed to visually present the interrelationships between different keywords extracted from the titles or descriptions of industrial designs. The relatedness between keywords is determined by estimating the probability of their co-occurrence, employing the methods proposed by Steijn (2017). The edges in the network chart represent the degree of relatedness, while the nodes represent the distinct keywords. The size of each node corresponds to the number of designs registered with the respective keyword, while the colour of the nodes reflects the concentration of relatedness within them. Consequently, a small-sized node with a dark colour indicates that the keyword is not extensively registered by industrial designs, but it exhibits a high degree of relatedness with other keywords.

2.4.1.10 Pie Chart

For data that has been divided into multiple categories, the proportion of each category in the total can be visualised using a pie chart. In the pie chart, the focus is on the share or proportion rather than the actual values. When the trend of the data has been presented in another type of chart, a pie chart can be used to show the cross-sectional values and highlight the proportions. This is a technique of data visualisation that is easy to understand, as it focuses on the proportion of the data rather than expressing more detailed information behind the data.

2.4.1.11 Radar Chart

Data can have multiple dimensions, and sometimes these dimensions are considered as different categories. For example, industrial designs are registered under different Locarno classes. These Locarno classes can be used as criteria to categorise the data, or they can be considered as dimensions of the global industrial design. If they are seen as categories, a bar chart is an effective way to illustrate the distribution of designs across different categories. On the other hand, if these categories are considered as dimensions of the global industrial design, a radar chart can be employed as a visualisation tool to present the distribution of industrial design in the Locarno classes.

A radar chart is also often called a spider chart or web chart. It is plotted on a two-dimensional plane with multiple equi-angular spokes, where each spoke represents a specific dimension or variable of the data. The data values for each variable are plotted along the corresponding spoke, and the resulting points are connected to form a polygon. Radar charts are useful for comparing the relative performance or characteristics of different variables across multiple categories. They are commonly used in fields such as market research, sports analysis, and performance evaluation.

2.4.1.12 Scatter Chart

A scatter chart consists of the vertical (y) and horizontal (x) axes, where observations in the dataset with corresponding x-values and y-values are plotted on the plane as scattered points. The scatter chart serves as the foundation for line or bar charts. It is important to note that when the scatter chart is plotted alone, multiple data points can be plotted at the same position determined by the x-value and y-value on the plane. Additionally, in order to classify different types of data points, colours or shapes can be used. While the scatter chart is not the most effective chart for exploring trends or specific patterns in data, it allows for the comprehensive understanding of the data in terms of two different variables by displaying all observations with their available x-values and y-values.

2.4.2 Application of Charts

It has been introduced different types of data visualisation techniques, in order to utilise these charts to explore the design data, the primary purposes of investigation needs to be specified. Firstly, this study aims to illustrate the change of industrial design registration in the world along with time, this can be conducted for different types of designs and for different countries. Secondly, at the country level, industrial design can be investigated both the owner countries and the protection territories. Lastly, since the industrial design can be registered under different Locarno classes, the distribution of industrial design in different Locarno classes can be explored, while this analysis can be combined with both the time trend as well as both owner countries and protection territories.

2.4.2.1 Time Trend of Industrial Design

The exploration of the time trend of industrial design registration focuses on the historical evolution of industrial design. From the year 1805, which is the earliest design record detected in the dataset, to the most recent year 2019, the application dates of design records can be extracted. For each date, the number of global design registrations can be computed on a daily frequency. By plotting the daily data with a time-series line, the evolution of industrial design can be shown from the perspective of quantity.

In order to distinguish different time periods in the evolution of industrial design, the historical and ongoing industry revolutions are used as criteria. The historical timeline of industrial design can be divided into four time intervals: before the second industrial revolution (1805-1869), the second industrial revolution (1870-1946), the third industrial revolution (1947-1999), and the fourth industrial revolution (2000-2019). The number of designs registered within each time interval can be computed and plotted in a pie chart to show the proportions of designs registered in each time interval among all historical designs.

2.4.2.2 Objects of Industrial Design

According to the available information in the original dataset, the investigation into objects of industrial design can be done primarily from two perspectives: (i) which Locarno classes designs are registered into; (ii) which keywords are involved in the description of designs. The exploration of industrial design across different Locarno classes is the benchmark analysis, due to the Locarno classification being a standardised and international classification used when registering designs. Thus, the original design record data can provide sufficient available information in terms of Locarno classes. However, the analysis of keywords involving text mining can only be done for design records that clearly identify the English designation of industrial design, resulting in a relatively low coverage rate.

A horizontal bar chart is employed to visualise how many designs are registered in corresponding Locarno classes, with the vertical axis representing Locarno classes and the horizontal axis representing the count of design registrations. The earliest design records with clear Locarno classes are from 1954, while the most recent design records with clear Locarno classes are from 2019. Therefore, the time range of analysis is limited to 1954-2019. Moreover, stacked bars with different colours filled from light to dark, according to the time periods from early to recent, are used to specify the amount of design registrations in different time periods.

Therefore, the bars representing different Locarno classes that appear darker indicate that the corresponding classes have been developed in recent years, while the overall lighter bars indicate that their corresponding classes were developed earlier. This enables the time trend to be visualised via colours, with the colour scale supporting grey-scale printing to ensure reader-friendliness.

Another stacked horizontal bar chart with a similar logic but different data is employed to present the keywords involved in design records. Here, the vertical (y) axis represents different keywords, while the horizontal (x) axis corresponds to the frequency of occurrence of these keywords. The keywords are extracted from the column *Designation in English* in the original dataset. Therefore, this information in design records used to generate this set of data has to be clearly identifiable. Thus, the time coverage of the analysis of keywords is different from the analysis of Locarno classes. The earliest design record with a clear English designation is from 1877, and the most recent one is from 2019. Therefore, the time range is limited to 1877-2019. Stacked bars are filled with colours from light to dark, according to the time periods from early to recent.

Furthermore, in addition to the separate analysis of keywords or Locarno classes, the most frequently mentioned keywords can also be investigated within different Locarno classes. Therefore, the most frequently mentioned keyword for each Locarno class can be extracted, and the corresponding frequency can also be computed. This is visualised using an identity bar chart with labels indicating the keywords and their frequency. This is still a horizontal bar chart, with the vertical (y) axis representing Locarno classes and the horizontal axis representing the frequency of keyword occurrence. Values are calculated based on all historical design records, with the most recent year being 2019 and the earliest year being 1877. Therefore, the cross-sectional values for 2019 are visualised without the time trend.

Since each Locarno class can cover a large number of keywords, and the same keywords can also be mentioned in different Locarno classes, different Locarno classes are connected to each other via common keywords. The relatedness between different Locarno classes can be visualised using a network plot, with the nodes representing different Locarno classes and the edges indicating the connections between them. The size and colour of nodes can be specified according to the degree of relatedness and the total count of design registrations for the corresponding Locarno classes. The network chart is also computed based on the cumulative design count during 1877-2019, without the change of time trend.

2.4.2.3 Distribution of Design Owners

The analysis of design ownership is conducted at the country level from two perspectives: the number of designs owned by different countries and the number of design owners in different countries. It is worth noting that design owners are identified at the individual or firm level. The term *designs owned by different countries* refers to designs whose owners are located in different countries. Through data visualisation of design ownership, a comprehensive understanding of the origin and dominating countries of global industrial design can be obtained.

The area chart is employed to illustrate the time trend of the extent to which various countries are dominating industrial design. The stacked area chart shows the time trend of the number of design registrations. The time unit is the year, allowing for the presentation of annual changes. Different colours are used, with darker colours representing countries with a higher number of designs owned. As the majority of designs are owned by a minority of countries, only the top owner countries are selected for separate illustration, while the rest of the world is regarded as a whole.

However, as only a limited number of single countries can be clearly presented on the area chart, the polygonal geographic map is employed to show the design registration of all available countries in the world. The geographic map visualises cross-section data instead of time trend. The maximum design protection duration of 25 years is used to specify the time interval for calculating the valid stock of designs for each year in different countries. The time points to be visualised can be selected based on the time trend presented in the area chart, such as the peak year or the year with a high increasing speed of industrial design registration.

In addition to the analysis from the perspective of the number of designs owned by different countries, the number of owners and the number of designs per owner in different countries can also be explored. The analysis of the number of owners focuses on the intensity of industrial design in the world, while the analysis of the number of designs per owner focuses on the intensity of design owners. To some extent, the intensity of design owners can more effectively illustrate the sustainable growth of industrial design than the current intensity of industrial design itself.

The data visualisation of the number of owners and the number of designs per owner is displayed via the combo chart, with two y-axes representing two different ranges of values. The number of owners is presented via the bar chart, and the number of designs per owner is presented via the line chart, on the same plane. To further show the global distribution of owners and the average number of designs per owner in each country, the polygonal world map is plotted using the cross-section data.

2.4.2.4 Target Market of Industrial Design

Industrial designs can be protected in specific countries through registration with international intellectual property (IP) offices such as ARIPO, BXIPO, EUIPO, and WIPO. Protection territories are determined by the national IP offices where the designs are registered. In cases where design applicants do not specify the protection territory, the designs will be automatically protected in the territory represented by the corresponding IP offices. Different countries worldwide represent different target markets of industrial design, the exploration of the popularity in terms of design registration countries can discover the dominating countries of industrial design from the perspective of target markets.

According to the available historical design records in the dataset, the cumulative number of design registrations from 1805 to 2019 can be calculated. In addition, as the protection territory can be detected, the cumulative number of designs registered to be protected in different countries during this time period can also be calculated. To visualise the overall variation across the world, the polygonal world map is employed. Besides, since the world map can only display the cross-section value, therefore, the time trend of design registration in different target markets can be displayed in the area map with different filled colours to represent the top countries.

To some extent, the popularity is a degree value instead of the amount value, therefore, rankings may help to visualise the popularity of different design markets. Selecting the dominating target markets, the cumulative number of design registrations in these markets can be computed for different time periods first, then, sorting these countries to get the rankings. The rankings of design target markets can be shown in the bump chart, the changes of rankings from one period to another are able to be visualised.

When involving the discussion of design protection territory, in the global market, design registrations can be divided into two categories, namely the national design registration which indicates the designs owned and protected by and in the same country, and the cross-border design registration which indicates designs are owned and protected by and in different countries. To identify the difference between these two categories of industrial design registration, the number of designs belonging to both types can be calculated separately. In comparison, cross-border designs and national designs can be plotted on the same chart with different colours.

In order to compare the quantity of cross-border and national design registrations, both stacked bar chart and the grouped bar chart are employed. To compare the proportions of two different types of design registrations possessed in the world, the stacked bar chart is used, with the x-axis representing the time with the unit of year. On the other hand, in order to compare the real value of the number of designs in the two types, the grouped bar chart is employed. In these bar charts, a light colour is filled into bars representing the cross-border designs, while a dark colour is filled into bars representing the national designs.

Furthermore, in the initial exploration of the original dataset, it can be found that a large number of cross-border designs are registered in the European market. Therefore, the European market can be selected as a category to analyse the cross-border designs. According to whether or not the owner countries or the protection territories belong to Europe, cross-border designs can be further divided into four groups. Namely, cross-border design owned by European owners and protected in Europe, owned by non-European owners and protected in Europe, owned by European owners and protected in non-European countries, and owned by non-European owners and protected in non-European countries.

With the interaction of two different colours and two different line types, these four groups can be presented in the same line chart. The owner country can be distinguished by colours, while the protection territory can be identified by the line type. Cross-border designs with European owners are represented by a dark colour, those with non-European owners are represented by a light colour. Cross-border designs protected in European countries are represented by the solid line, while those protected in non-European countries are represented by the dashed line.

Besides, as designs can be divided into two primary groups according to whether or not the owner country is the same as the protection territory, meanwhile, the cross-border designs can be further divided into four groups according to whether or not the owners or the protection territories belong to Europe. In order to investigate the objects of designs registered in different markets, these six groups of designs can be plotted on the radar chart with the equi-angular spokes representing 33 Locarno classes (at the 2-digit level).

2.5 Results

The results section aims to present the global pattern of industrial design registration through data visualisation. To illustrate this pattern from different perspectives, based on the features of industrial design as an intellectual property, the section is divided into four parts. Firstly, the overall trend of the evolution timeline of industrial design is explored by examining the time trend of registered designs globally. Secondly, the distribution of designs across different Locarno classes or keywords extracted from design titles or descriptions is investigated to understand the objects for which designs are registered. Thirdly, the distribution of design ownership worldwide is illustrated to analyse the global ownership distribution. Lastly, the protection countries of industrial design are considered as the target markets to be investigated, as designs need to be registered in specific territories to be protected.

2.5.1 Overview of the Design Registration Timeline

To gain an overview of the development of industrial design globally, analysing the time trend of increasing design registrations provides a reasonable approach for placing industrial design on a timeline. This allows for the examination of the increase or decrease of industrial design during different time periods.

The daily count of design registration from 1805 to 2019 is presented in Figure 2.1. The timeline is divided into four parts based on the Second Industrial Revolution[1], the Third Industrial Revolution[2], and the ongoing Industry 4.0[3]. Additionally, the graph includes straight lines representing the daily average count of design registration during different time periods.

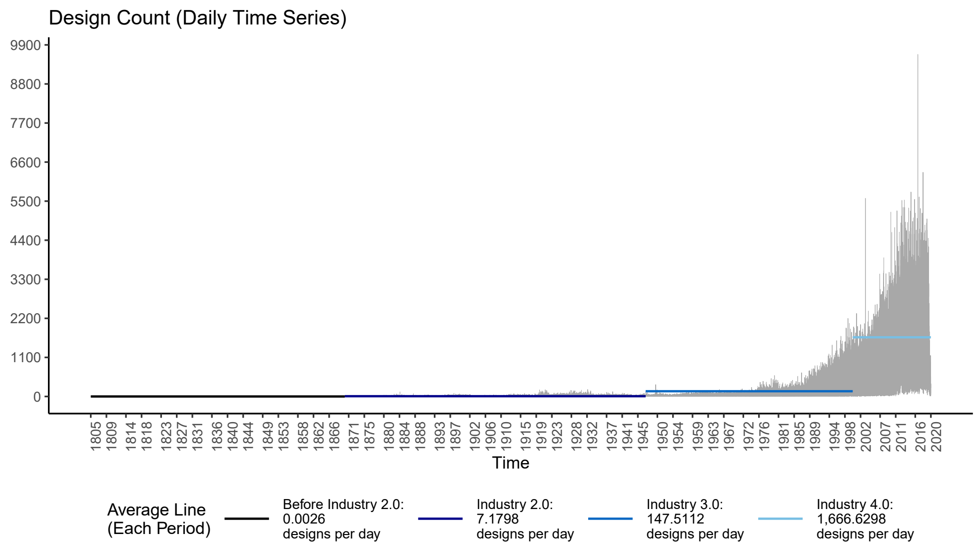


Figure 2.1: Line Chart - World Daily Design Registration (1805 - 2020)

[1]The Second Industrial Revolution is defined as the time period of 1870-1946
[2]The Third Industrial Revolution is defined as the time period of 1947-1999
[3]Industry 4.0 is considered to start in 2000

From Figure 2.1, it is evident that the first recorded design registration in this dataset occurred in 1805, prior to the second industrial revolution. Furthermore, there is a clear increasing trend in global industrial designs, as indicated by the overall upward trajectory of the daily count of design registrations. The computed daily average for different time periods reveals a distinct stepwise increment in industrial design from the onset of the second industrial revolution, through the third industrial revolution, and into the ongoing Industry 4.0.

Comparing the number of design registrations during each time period (before the second industrial revolution, the second industrial revolution, and the third industrial revolution), it is clear that the count is significantly higher in the ongoing Industry 4.0. To visually represent the proportion of designs registered during each period relative to the entire timeline, a pie chart is plotted in Figure 2.2.

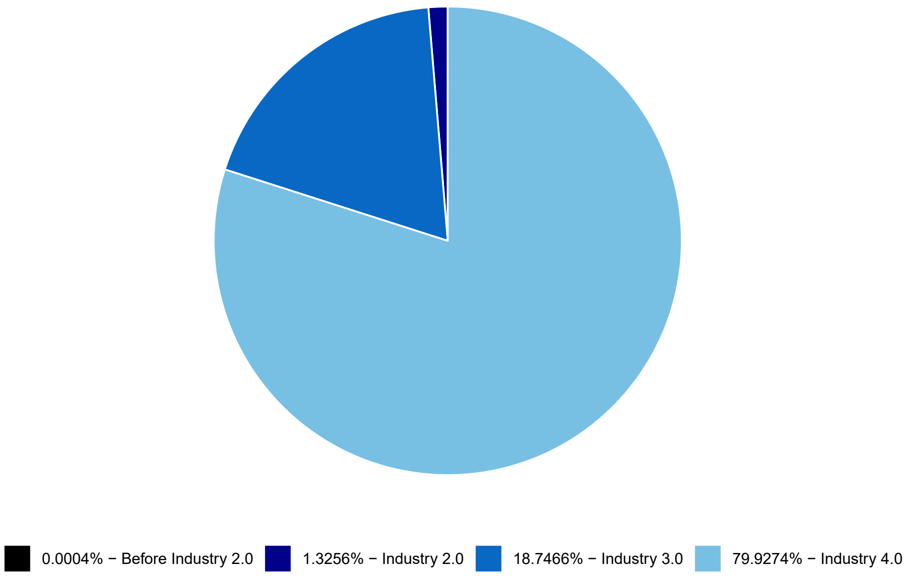


Figure 2.2: Pie Chart - Percent of Designs Registered in Different Periods

From Figure 2.2, several observations can be made. Firstly, the number of designs registered before is negligible, indicating the early stages of industrial design development, which predates the significant period of industrial design advancement. Secondly, the proportion of registered designs during the second industrial revolution is relatively small in relation to the overall historical total. However, the average daily count of 7.9 registered designs suggests a healthy and stable increase in industrial design during this time period. Thirdly, the first significant increase in global industrial design occurs during Industrial 3.0, implying a parallel development with technological advancements. Lastly, the registered industrial designs account for approximately 80% of the total, indicating a substantial growth in industrial design following the initial peak during Industry 3.0.

2.5.2 Different Categories of Industrial Design Registered Worldwide

The registration of industrial design involves designating designs for various applications or usages, which are classified according to the international standard classification known as Locarno classes. Additionally, an analysis of the titles or descriptions of the registered designs can provide insights into their intended usage. This section aims to explore the extensive registration of designs by analysing both the design designation and the Locarno classes. The analysis is conducted on a global scale to observe variations in design distribution across countries and to examine changes in the popularity of different designs over time.

2.5.2.1 Exploration by Locarno Classes

When registering, applicants need to specify the industrial designs as one or multiple types, while the design type is defined as Locarno classification which is the international standard design classification. By analysing the amount of industrial design registered under each Locarno class, it can be seen which design types are frequently registered, and to some extent, the popularity of different designs in the market can be discovered.

Figure 2.3 is the horizontal stacked bar chart, where the x-axis represents the values of design count, while the y-axis indicates the different 33 Locarno classes at the 2-digit level. The stacked sub-bars indicate the design count in different time periods, which are filled with different colours. The lighter colours represent the earlier years, while the darker colours indicate the more recent years. Thus, the bars with more dark colours mean that these categories of designs were developed in more recent years, while if the bars are in lighter colours, it means that these categories of designs were developed in earlier years. The total length of the bar represents the amount of registered designs during 1854-2019.

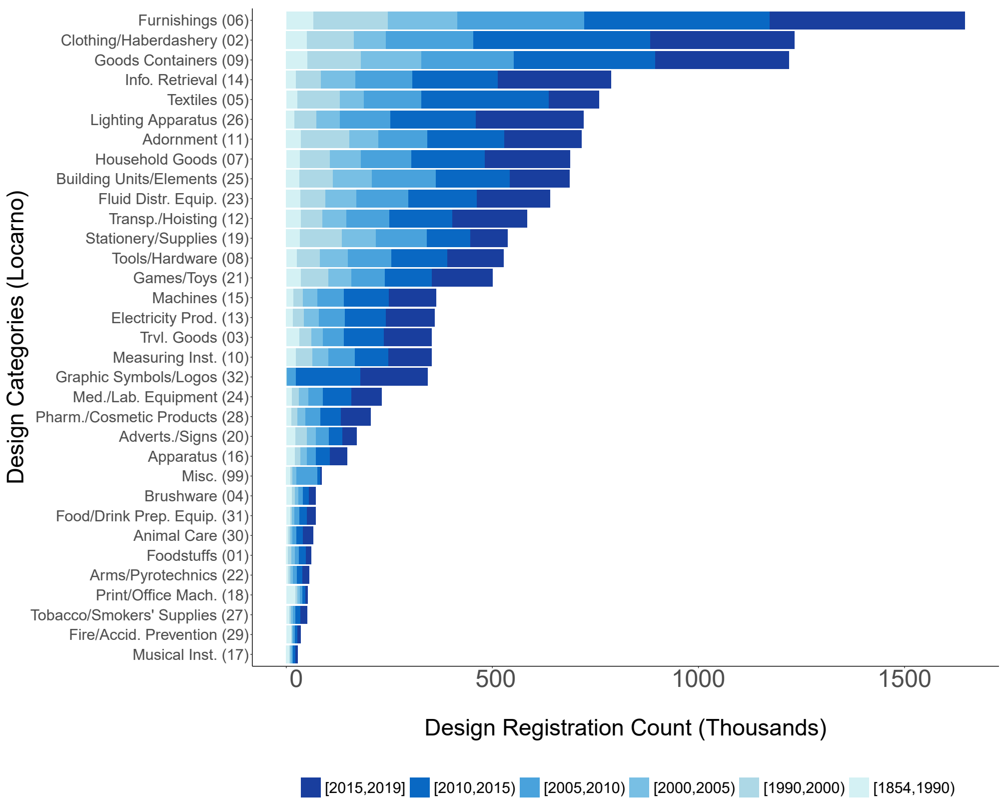


Figure 2.3: Bar Chart - Design Registration in Locarno Categories (1854-2019)

In Figure 2.3, it can be seen that the most registered design classes are Locarno *06* (furnishing) and Locarno *02* (clothing). Considering that industrial design protects the appearance of articles, it is evident that a significant number of designs are registered to protect manufactured goods, including furnishing and clothing. Additionally, the industrial design for goods containers (Locarno *09*) is also registered more frequently than other types of designs. This indicates the close relationship between industrial design and manufacturing industries.

Furthermore, the number of registered designs for information retrieval products and electricity products is relatively higher than other types of designs. As mentioned in the previous analysis, the development of industrial design reaches its peak during Industry 4.0. With the advancements in technology during this period, the corresponding industrial design for high-tech goods is also rapidly evolving.

Additionally, the first registered designs of graphic symbols and logos occur during the period of 2005-2010. This is because industrial design of graphic symbols was defined as a separate Locarno class in the 9^{th} edition of the Locarno classification, which was issued in 2008. Prior to that, all designs of graphic logos or symbols were classified under Locarno class *99* (miscellaneous). This is also why Locarno class 99 appears in lighter colours, suggesting that designs in this class were developed in earlier years.

2.5.2.2 Exploration by Occured Words

In addition to analysing the count of different Locarno classes, it is also valuable to investigate the description of industrial designs. This can be done through text mining, where individual words are extracted from the design description and stored in the variable *designation in English* in the raw dataset. Once the single words are extracted, their frequency of occurrence can be computed. The earliest design record with clear designation information dates back to 1877, therefore, the analysis of words can begin from that year.

Similar to the analysis of Locarno classes, we can start by identifying the top words that frequently appear in the dataset. These top 20 words represent different categories, and the number of designs containing each word can be calculated, defining the frequency of word occurrence. To explore the distribution of different words across time periods, the design count is computed for each time interval, using the same time intervals as in the analysis of Locarno classes.

Figure 2.4 presents a stacked bar chart where the vertical axis is labelled with the top 20 words that frequently appear in the designations of designs. The horizontal axis represents the frequency of word occurrence. Since the values are calculated for different time periods, each period is filled with a different colour. Darker colours indicate more recent years, while lighter colours represent earlier years. Therefore, if the entire bar is predominantly in light colours, it suggests that designs with designations containing these words were developed in earlier years. Conversely, if the bar is mostly composed of dark colours, it indicates that designs with designations of these words were developed in more recent years.

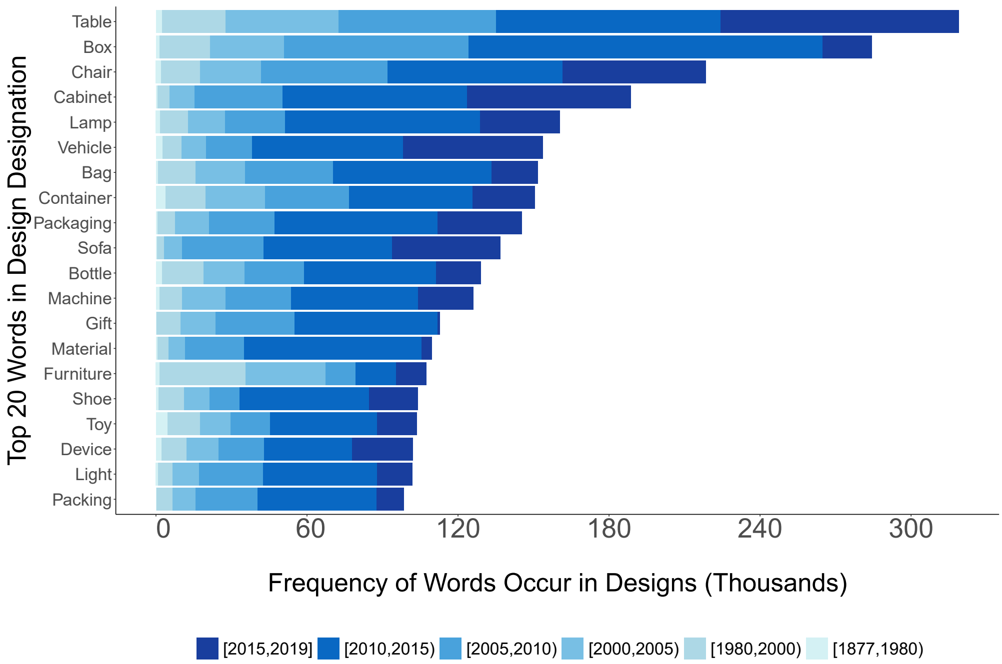


Figure 2.4: Bar Chart - Frequency of Words Occurrence in Design Designation

From Figure 2.4, the prominent keywords designated for designs are closely tied to various aspects of people's lives and commodity trade. The majority of designs focus on furnishings that are integral to daily life, while designs for packaging, boxes, and containers aim to facilitate trade in goods. Design, in essence, is about enhancing and improving life, especially in conjunction with technological advancements.

Additionally, it is evident that designs designated for furniture were more prevalent in earlier years, whereas designs for sofas and cabinets have seen a surge in recent years. Notably, all these keywords, including furniture, cabinet, and sofa, fall under the Locarno class of furnishings. Hence, this observation suggests that as industrial design evolves over time, designs become increasingly specialised.

Furthermore, it is worth conducting an analysis of the top words within each Locarno class. This approach allows identifying the predominant designs within each class. Moreover, different Locarno classes may share common keywords, indicating a relationship between them. By employing text mining techniques, the associations between various pairs of Locarno classes can be explored. Thus, the subsequent sections will delve into the examination of the top words within each Locarno class.

2.5.2.3 Intersection of Occurred Words and Locarno Classes

Previous analysis has examined the popularity of Locarno classes in existing designs and the level of involvement of specific words in these designs. This approach allows for the identification of the primary objectives of the designs. Additionally, the occurrence frequency of different key words varies across each Locarno class. Consequently, identifying the top key word in each Locarno class can facilitate the discovery of corresponding design themes.

Figure 2.5 presents two dimensions: the vertical axis represents the Locarno class, while the horizontal axis represents the occurrence frequency of the top-one word in each Locarno class. The length of the horizontal bar denotes the occurrence frequency of the class-specific top-one word, which is accompanied by its label and frequency. The data utilised in this graph is derived from global design records spanning the period from 1877 to 2019, with the frequency of occurrence being cumulative.

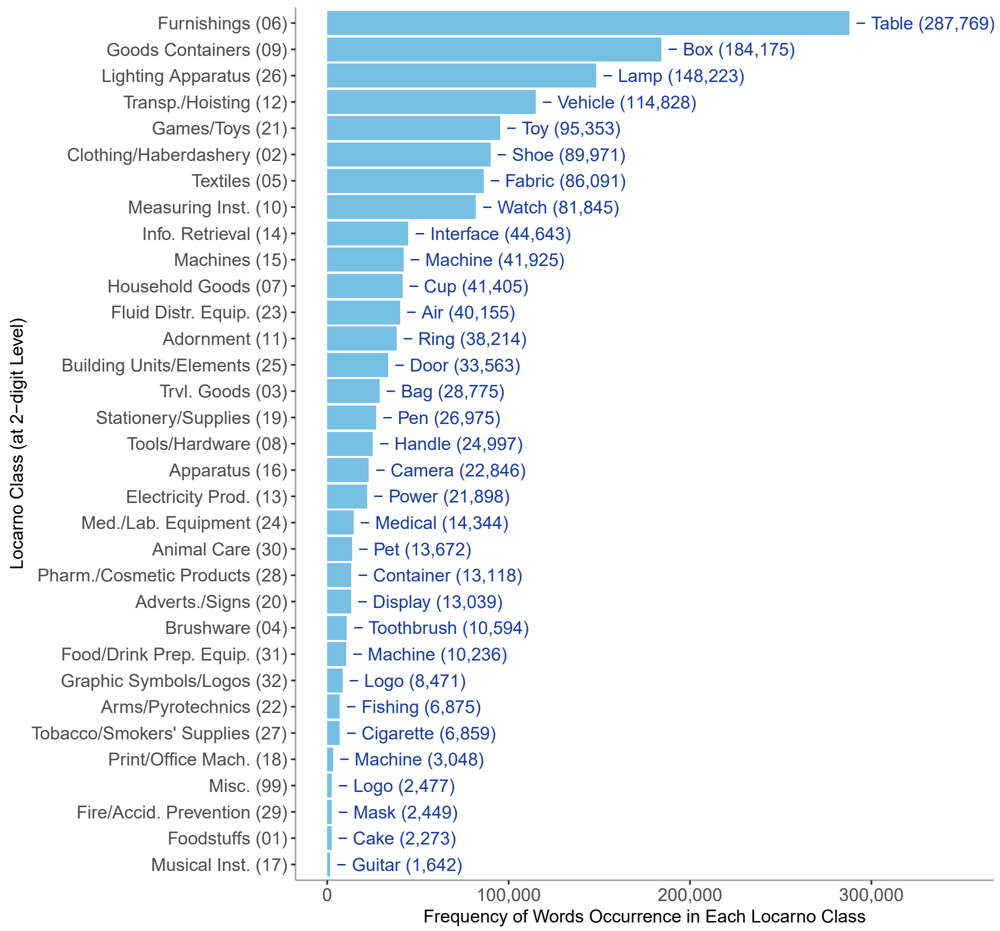


Figure 2.5: Bar Chart - Top Words of Each Locarno Class (Statistics During 1877-2019)

Figure 2.5 reveals that the term *Table* and its corresponding Locarno class *Furnish-*

ing (06) continue to exhibit remarkable popularity. The analysis of previous findings indicates that other prominent terms, such as *Cabinet*, *Furniture*, and *Sofa*, predominantly feature within the Locarno class associated with furnishing. Furthermore, this figure provides an overview of the top words across all 33 Locarno classes. Notably, the term *Logo* emerges as the most frequently encountered word in both the Locarno class pertaining to graphic symbols and the Locarno class encompassing miscellaneous designs. Consequently, early designs for logos were initially classified within the miscellaneous category. However, with the development of the design patent system, these newly produced logo designs were subsequently specified under the class of graphic symbols.

2.5.2.4 Relatedness within Locarno Classes

In the examination of design data, it becomes apparent that certain words are commonly shared across different Locarno classes. This observation suggests that different Locarno classes can be interconnected through shared key words. Analysing these shared key words offers a potential avenue for investigating the interconnectedness among various Locarno classes. To visualise the multidirectional interconnectedness between different Locarno classes, a network chart is employed.

Figure 2.6 represents a network chart that extends beyond the conventional two-dimensional plane formed by the x and y axes. The circular nodes within the chart symbolise the 33 distinct Locarno classes, serving as the anchor points of the network. The straight lines connecting these nodes, referred to as edges, depict the relatedness between different Locarno classes. The colour of each node is determined by the number of edges connected to it, with lighter to darker shades indicating a lower to higher degree of association. Additionally, the size of each node corresponds to the total count of designs within the respective Locarno class in the raw data. Lastly, the interconnectedness between nodes generates forces, resulting in the concentration of core nodes in the central position of the graph, while others are positioned towards the periphery. The computation underlying this figure is based on the raw design records spanning the period from 1877 to 2019.

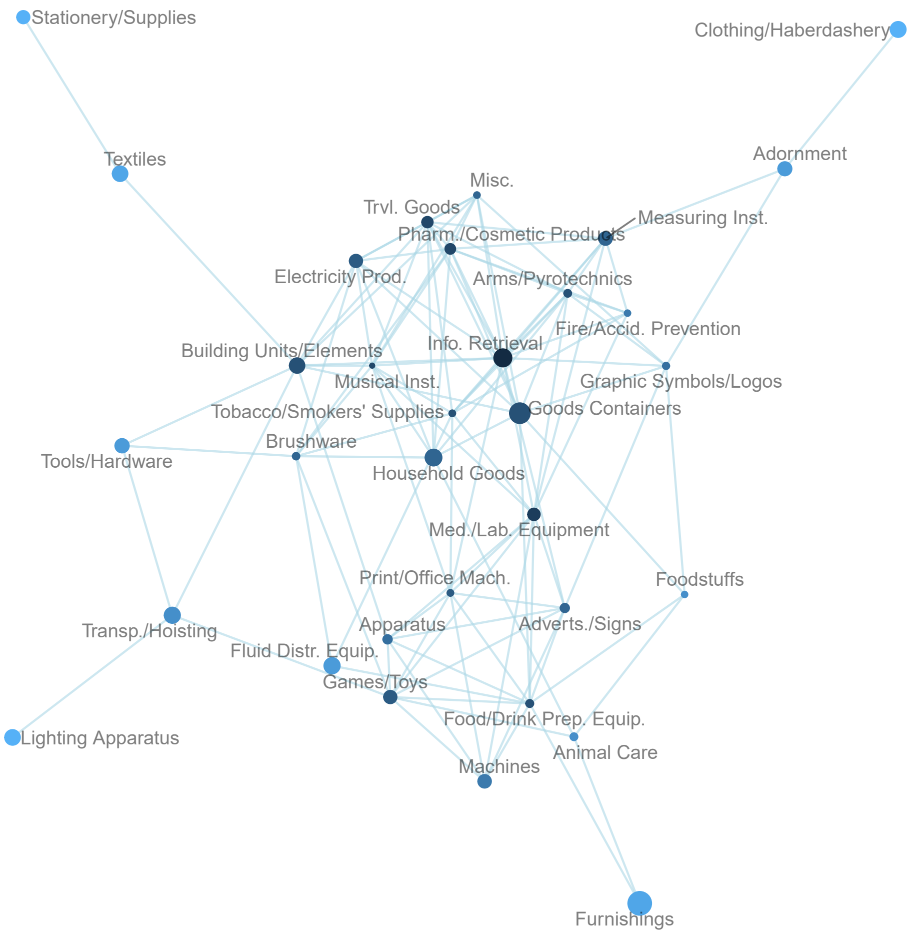


Figure 2.6: Network - Relatedness within Locarno Classes

Based on the findings presented in Figure 2.6, it is evident that Locarno classes with a substantial number of designs do not necessarily occupy the core nodes. For instance, the Locarno classes associated with furnishings, clothing, and lighting apparatus encompass a significant proportion of registered designs. However, due to their limited connectedness with other Locarno classes, they do not hold a core position. Conversely, certain nodes with smaller sizes but darker colours occupy the core position due to their high level of relatedness with other nodes.

Moreover, the Locarno classes with the highest degree of relatedness are information retrieval and medical equipment. These two corresponding nodes serve as the core anchors in this network. Therefore, despite industrial design primarily focusing on enhancing people's daily lives, as evidenced by the large number of designs for clothing, furnishings, and goods containers, the core designs still predominantly involve high-tech products.

In brief, it is evident that industrial design for information retrieval stands out as the core category, indicated by its darker shading in Figure 2.6. This suggests that while there exists a significant disparity between design rights and patent rights in the context of legal protection for intellectual property (IP), the most pivotal design category, which is most closely related to other designs, is closely linked to technical industries.

Furthermore, designs for goods containers and furnishings dominate the majority of the market. This implies that due to the inherent nature of industrial design rights, which protect the appearance of articles, the majority of designs are created for external packaging of goods or items like furniture, which heavily rely on their aesthetics to attract consumers.

In summary, it can be inferred that industrial design is driven both by technical advancements, as evidenced by the core industrial design being for information retrieval, and by meeting market demands. This is evident in the large number of designs created for goods containers, aiming to facilitate the sale of existing products. Additionally, industrial design is influenced by the aesthetic preferences of consumers, with furnishing designs holding a significant share of the market.

2.5.3 Distribution of Design Owners

The pattern of design ownership worldwide is examined in this section, focusing on the features of industrial design as an intellectual property. The analysis is divided into different aspects to explore the intensity of registered industrial designs owned by specific countries, the number of design owners in each country, and the distribution of different types of designs across countries and Locarno classes.

The first aspect examines the intensity of registered industrial designs owned by specific countries. This analysis considers the cumulative number of design registrations for each country and explores the variation in design ownership over time. The results are presented in terms of the number of designs owned by each country, highlighting the countries with the highest intensity of design ownership.

The second aspect focuses on the number of design owners in specific countries. This analysis considers the total number of owners in each country and examines the distribution of design ownership across different countries. The aim is to identify the countries with the highest number of design owners and understand the concentration of design ownership within these countries.

The third aspect considers the different types of designs and their ownership distribution across countries and Locarno classes. The analysis combines the number of designs owned by each country with the Locarno classes to which these designs belong. This allows for an examination of the distribution of designs across different countries and design categories, providing insights into the preferences and strengths of each country in terms of design ownership.

By exploring these different aspects of design ownership, we can gain a comprehensive understanding of the patterns and trends in design ownership worldwide. The analysis provides valuable insights into the intensity of design ownership in specific countries, the concentration of design ownership within countries, and the distribution of different types of designs across countries and design categories.

2.5.3.1 Number of Design Holdings by Countries Worldwide

Design patents are typically owned by individuals or firms, and by analysing their addresses at the country level, it is possible to explore the ownership of designs. In this set of analyses, the focus is on examining the time variation in the number of designs owned by different countries and identifying the countries that own the majority of designs worldwide. To accomplish this, an area chart is employed, with the total area stacked by individual areas representing different countries. The value-axis represents the number of designs registered each year.

Figure 2.7 comprises both the x and y axes. The x-axis represents a timeline measured in years, while the y-axis represents the design count. The number of design registrations by different owner countries is calculated for each year, and each country has a designated area plot on the graph. The stacked area of all countries represents the total number of designs worldwide. In this figure, the top 19 owner countries are identified, while the remaining owner countries are considered as a whole. The time period for this analysis is limited to the years 1990-2019, as the long historical timeline of industrial design development is not suitable for the targeted analysis.

In total, 20 colours are designated to represent these countries. Countries that own more designs are filled with lighter colours, while those with fewer designs are filled with darker colours. Countries with more designs are positioned at the top of the stacked area plot, while those with fewer designs are placed at the bottom. The stacked area plot is arranged in a top-down, dark-to-light colour distribution. The legend provides information on the proportion of designs owned by different countries relative to the world, along with their corresponding colours.

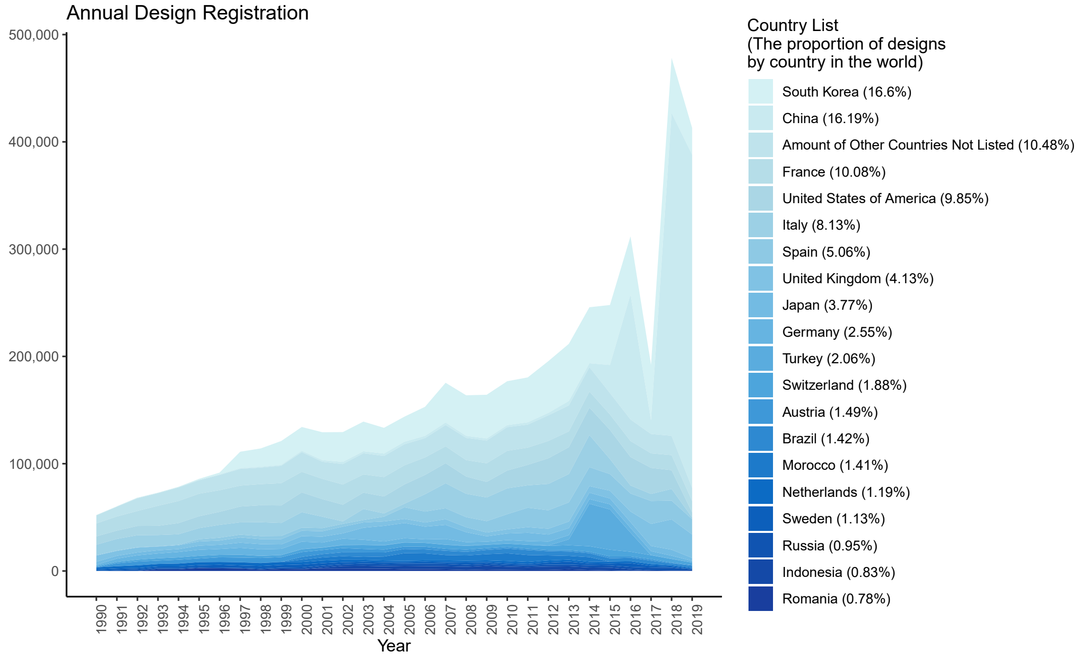


Figure 2.7: Area Chart - Annual Design Registration of Owner Countries (1990-2019)

Figure 2.7 presents a list of the top countries based on the number of designs they own. Notably, South Korea and China emerge as the primary owners of designs worldwide. In fact, the number of designs owned by these two countries surpasses the combined total of designs owned by all other unlisted countries. Additionally, the United States and various European countries, including the United Kingdom, constitute the second tier of design owners. Furthermore, distinct colour ridges are observed in 2007 and 2014, indicating peaks in design registrations during these years. Interestingly, the top two countries, South Korea and China, exhibit an increase peak with a one-year lag, distinguishing them from other countries.

In addition to the temporal trends depicted in the area chart, the cross-sectional analysis of registered design stock count provides insights into the variation in design ownership across countries. To achieve this, a suitable approach is the utilisation of a polygonal world map. By selecting a specific year as a reference point, the stock design count for different countries can be represented using distinct colours based on the number of designs. The stock count of registered designs is determined by considering the application date and the duration of protection, which is typically a maximum of 25 years. Consequently, for a given year, the stock count represents designs registered within the previous 25 years.

Figure 2.8 showcases the stock count of designs held by individuals and firms worldwide in the year 1990, encompassing the cumulative registered designs over the preceding 25 years (including 1990). The world map portrays the intensity of design ownership for each country, with darker colours indicating higher levels of ownership and lighter colours representing lower levels. Notably, in the early years, Europe emerged as the most developed region in terms of industrial design, with France leading in terms of design ownership. Additionally, the United States, Canada, and Japan also held a substantial number of designs. However, it is worth noting that numerous countries still had no registered designs at that time.

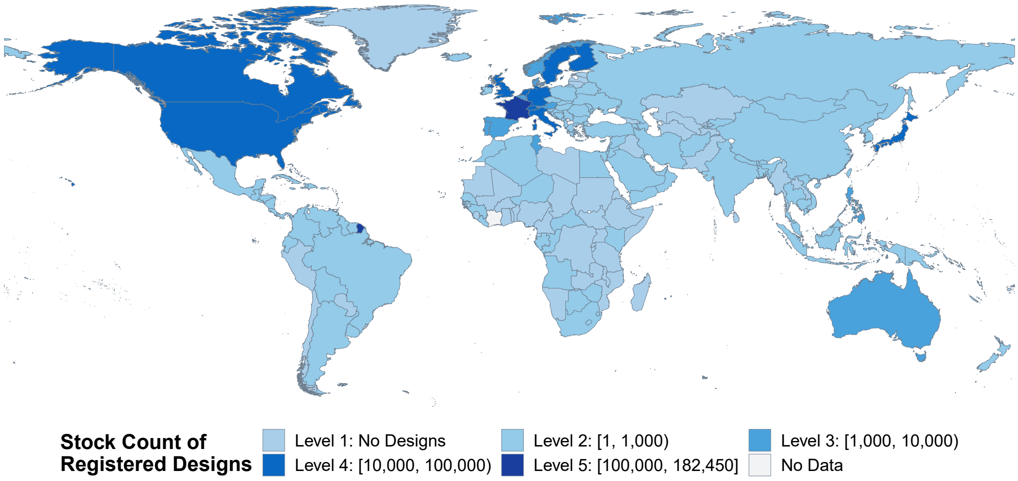


Figure 2.8: World Map - Stock Count of Design in Owner Countries (1990)

In line with the previous discussion, the year 2007 witnessed a notable peak in the trend of design registrations. To illustrate this, Figure 2.9 presents the cross-sectional stock count of designs across different countries, using 2007 as a reference point. When compared to Figure 2.8, a significant change is observed in the overall colour distribution on Figure 2.9, with darker colours indicating an increase in global industrial design registrations from 1990 to 2007. European countries continue to dominate in terms of industrial design, with the United Kingdom, Germany, and France emerging as the top-level owners. Additionally, the United States remains a leading country in industrial design. In Asia, South Korea and Japan are emerging as major contributors to the global design landscape.

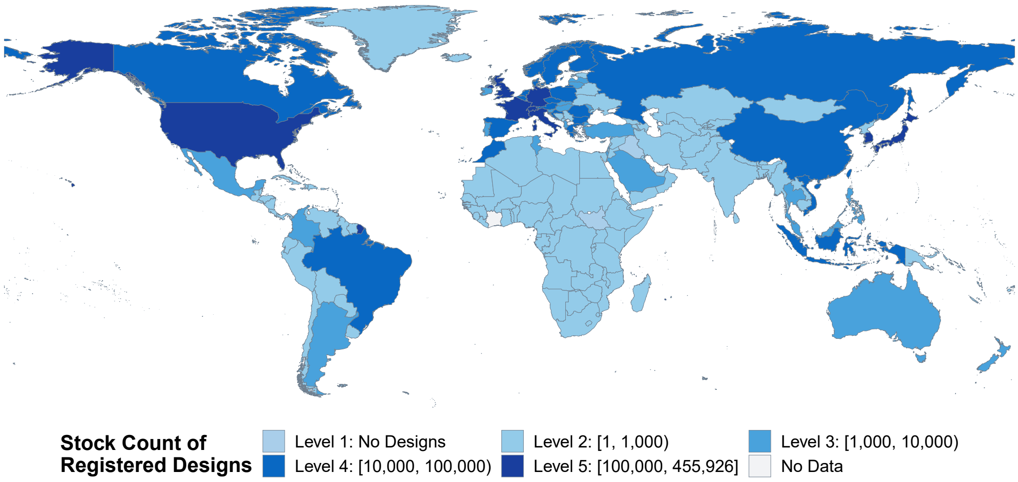


Figure 2.9: World Map - Stock Count of Design in Owner Countries (2007)

Moreover, with the occurrence of a second prominent peak in 2014, the polygonal world map is generated for this specific year (refer to Figure 2.10). Surprisingly, the observed difference between 2007 and 2014 does not exhibit statistical significance. One potential explanation for this unexpected outcome is the utilisation of a stock count measure for industrial design, which considers a cumulative time interval of 25 years. Consequently, to unveil the present distribution of design ownership, it is advisable to conduct the subsequent analysis using the most recently available cross-sectional stock count of industrial design, which corresponds to the year 2019.

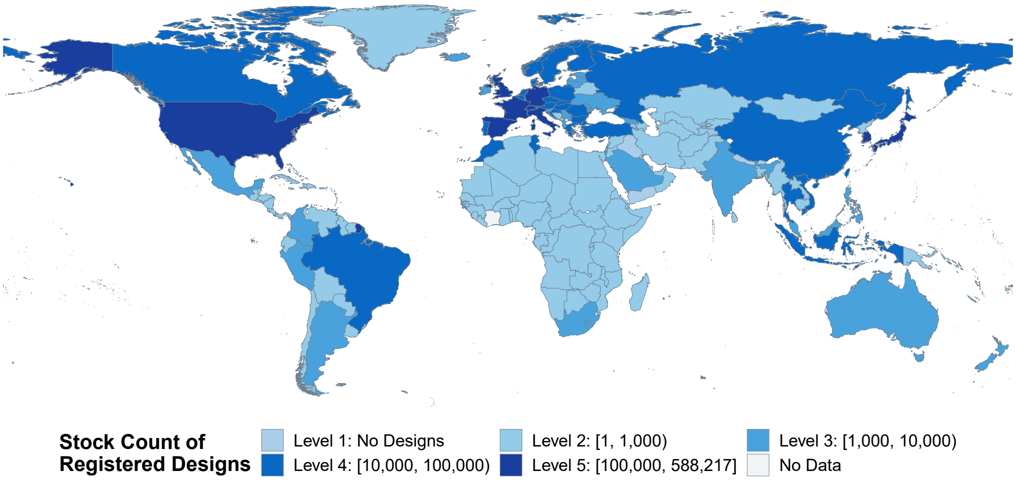


Figure 2.10: World Map - Stock Count of Designs in Owner Countries (2014)

The global peak in industrial design registrations is visually represented by the polygonal world map in 2019 (refer to Figure 2.11). A notable change from previous years is the extensive coverage of industrial design ownership across the world, excluding countries with unavailable data. All countries are depicted with darker colours, indicating a higher intensity of registered designs. European countries continue to dominate, with emerging EU countries such as Spain and Italy emerging as prominent owners of industrial design. Additionally, China has surpassed all other countries in terms of the number of designs owned, while other Asian countries including South Korea and Japan also hold significant shares in industrial design ownership.

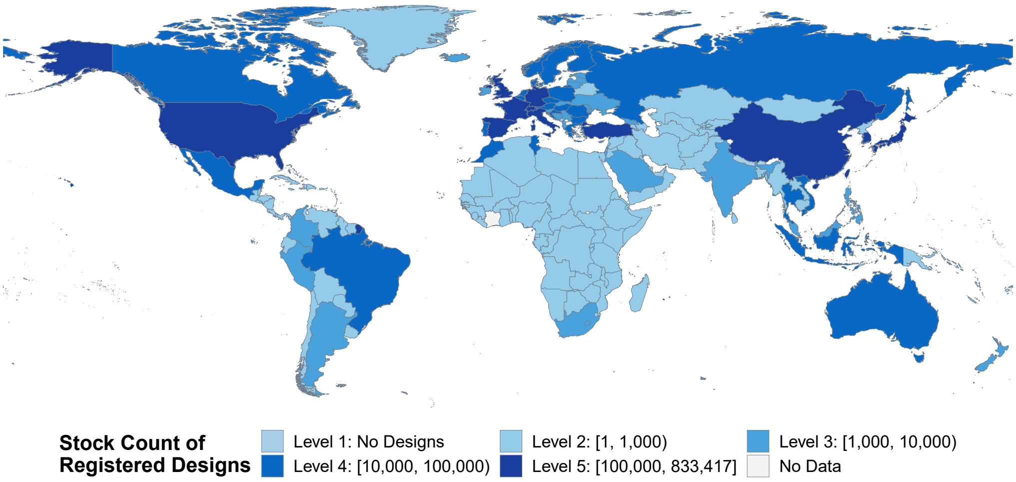


Figure 2.11: World Map - Stock Count of Design in Owner Countries (2019)

Based on the aforementioned data visualisation and analysis, it can be asserted that industrial design has exhibited a substantial growth trajectory from earlier years to the present. The dominant region in terms of design ownership is Europe, encompassing the United Kingdom. Additionally, notable countries such as China, the United States, South Korea, and Japan also demonstrate a significant presence in the ownership of designs. However, it is important to acknowledge that the analysis primarily focuses on the quantity of industrial designs. It is plausible that a few firms within a specific country may possess the majority of these designs. Moreover, the high concentration of design ownership may be a consequence of firms with a strong foothold in the industry, which is inherently influenced by the size of their respective economies. Consequently, to evaluate the level of development among countries in terms of design ownership, it is imperative to thoroughly examine both the number of design owners and the quantity of designs owned per owner.

2.5.3.2 Intensity of Design Holders Worldwide

In addition to analysing the stock design count across various owner countries, it is also essential to calculate the number of owners in different countries to examine the distribution of design owners worldwide. Subsequently, the design count per owner can be easily computed by dividing the total design count in a given year by the number of design owners. To observe the temporal trends in the increase or decrease of design owners and the design count per owner, the global total design count and owner count should be calculated for specific years. These results can be effectively presented using a combo chart that incorporates both a bar plot and a line plot.

Figure 2.12 displays two y-axes, representing the number of design owners and the number of designs per owner, respectively. The x-axis represents the timeline in years, allowing for the simultaneous plotting of bars and lines on the same plane. Light-coloured vertical bars indicate the number of design owners, with corresponding values labelled on the left-side vertical axis. The dark-coloured line plot represents the number of designs per owner, and the values are labelled on the right-side vertical axis. The timeline is limited to the period from 1990 to 2019, consistent with the time interval depicted in the previous area chart for the number of designs in different countries (Figure

2.7).

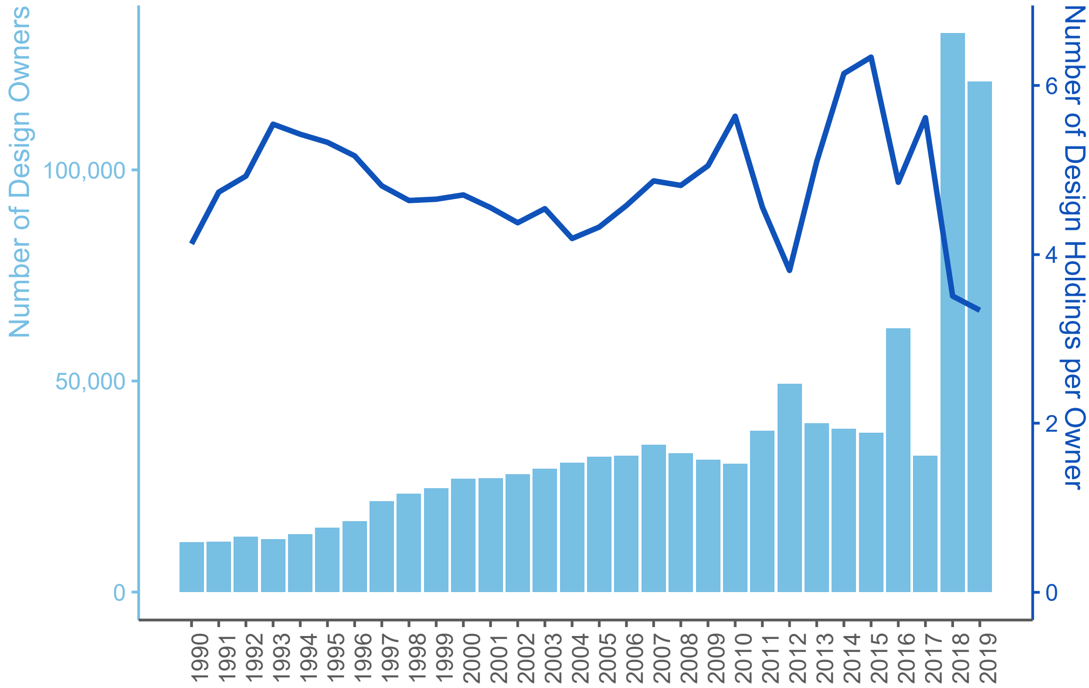


Figure 2.12: Bar-line Combo Chart - Number of Design Owners and Number of Designs Per Owner (1990-2019)

Based on the information provided in Figure 2.12, it is evident that the total number of global design owners has been consistently increasing over time. Conversely, the design count per owner exhibits a declining trend. This observation suggests that while the number of design registrations has shown an upward trajectory from 1990 to 2019, the increase in design owners has outpaced the growth in the total number of design registrations. However, it is important to note that the combo chart does not provide insights into the distribution of owners across countries. To address this, the polygonal world map is utilised to visually represent the distribution of owners worldwide.

The stock count of design owners can be computed by considering the 25-year protection duration of industrial designs and the application date. Once the values for each owner country in a specific year are determined, they can be represented as colours on the polygonal world map. Figure 2.13 illustrates the stock count of design owners for the year 2019, presenting the cumulative number of unique design owners over the past 25 years, including 2019. From this figure, it is evident that China, South Korea, and the United States exhibit a high density of design owners. Other significant countries, such as European nations, Japan, and Brazil, occupy the second largest tier in terms of design ownership.

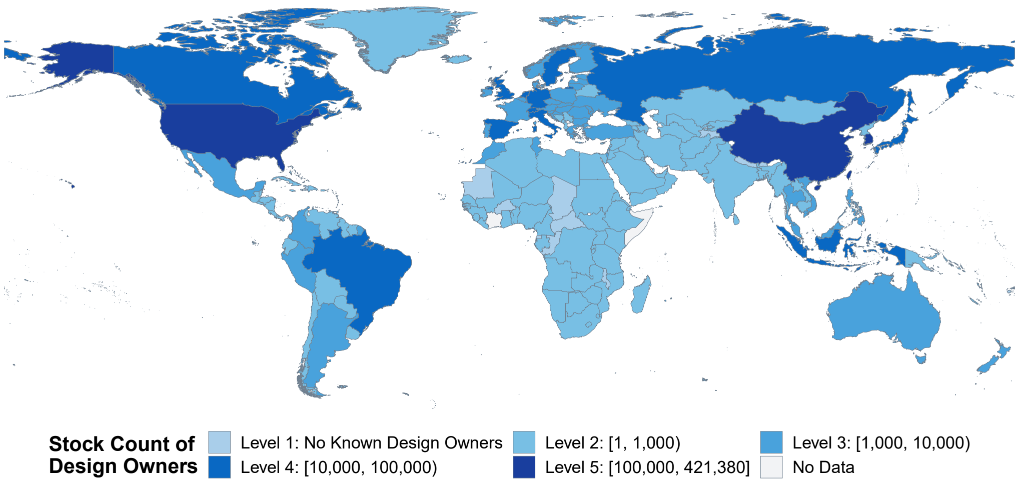


Figure 2.13: World Map - Stock Design Owners of Countries Worldwide (2019)

Upon examining the world map depicting the stock count of designs in 2019 (Figure

2.11), it becomes apparent that European countries exhibit the highest level of design intensity on a global scale. This observation prompts further investigation into the stock design count per owner, utilising the same protection duration. Figure 2.14 illustrates the stock count of designs per owner. Countries represented by darker colours indicate that a small number of firms or individuals possess a large number of designs, indicating a significant disparity in the distribution of design ownership within these countries. Conversely, countries represented by lighter colours suggest that a larger number of distinct firms or individuals own a relatively small number of designs, implying a relatively smaller disparity in the distribution of design ownership within these countries.

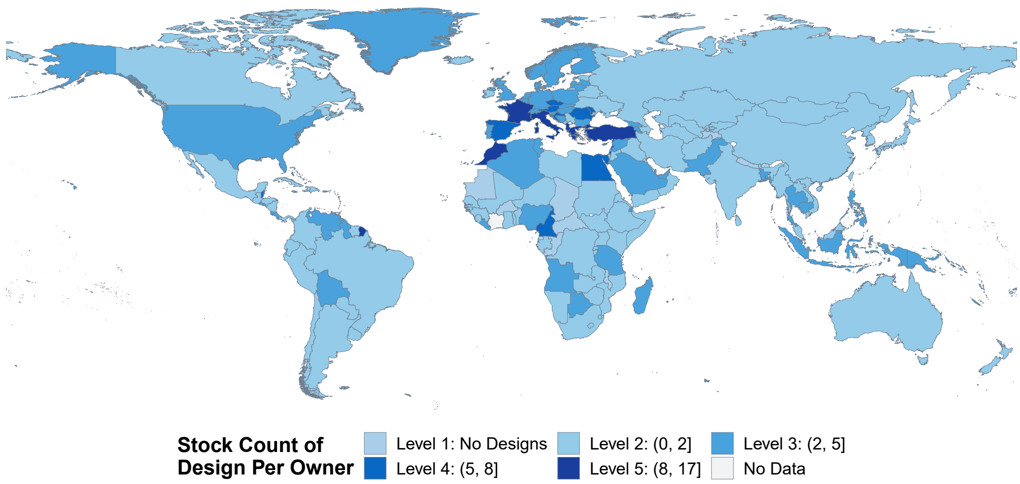


Figure 2.14: World Map - Stock Design Count Per Owner (2019)

Figure 2.14 exhibits a stark contrast to the world map depicting the owner count by countries. The predominant light colour indicates that the design count per owner for the majority of countries falls within the range of (0, 2]. Notably, France, Italy, Morocco, Greece, and Turkey demonstrate a concentration of designs among a few owners, resulting in a higher value of design count per owner. Conversely, China, South Korea, and Japan, as prominent countries in industrial design, exhibit a lower level of design count per owner, indicating that designs in these countries are widely owned by a larger number of distinct firms or individuals.

However, while the world map of design count per owner effectively portrays country-level variations, it fails to depict the relationship between the number of designs owned and the number of design owners. To address this limitation, utilising 2019 as the cross-sectional time point, the relationship between the stock count of designs and the stock count of design owners can be presented in a scatter chart. Additionally, by incorporating marginal histograms, the density distribution of both design stock count and design owner stock count can be illustrated.

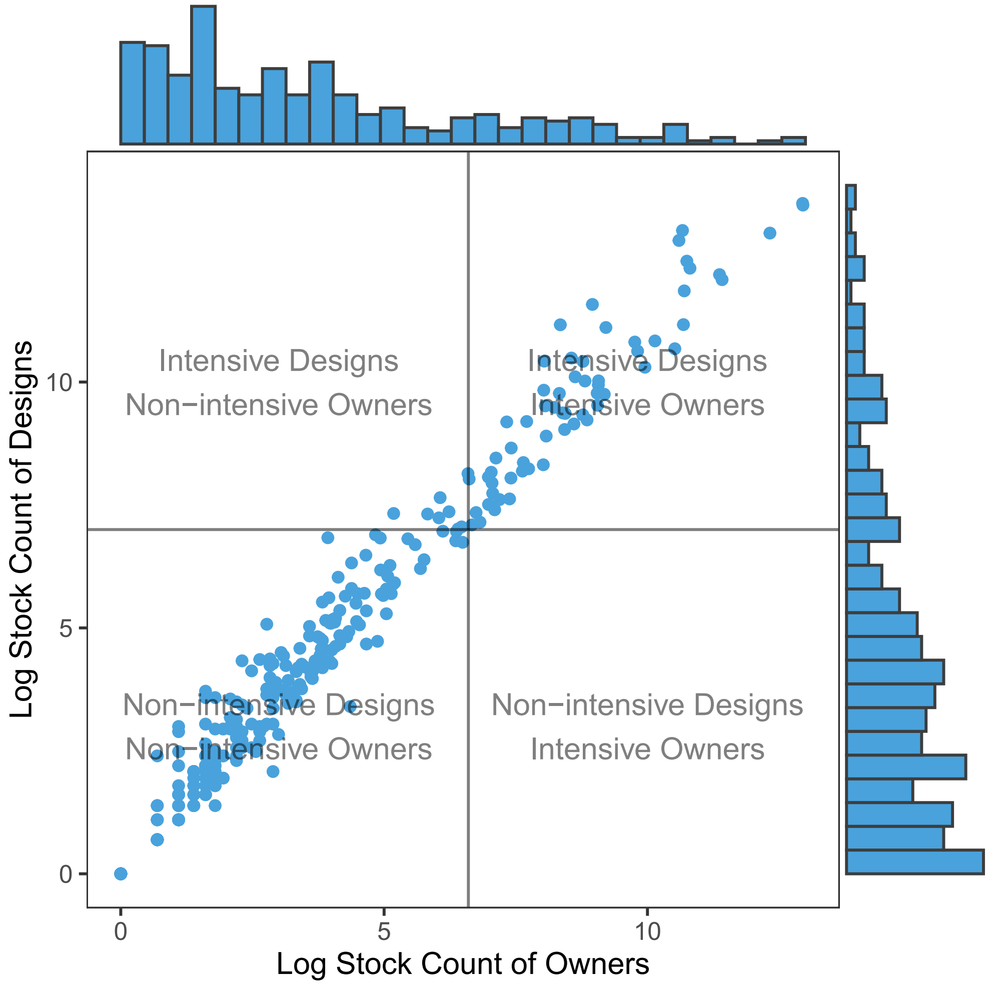


Figure 2.15: Scatter Chart with Marginal Histogram - Stock Count of Designs and Owners (2019)

Figure 2.15 presents scatter plots representing different countries worldwide, with the y-axis representing the logarithm of the stock count of designs and the x-axis representing the logarithm of the stock count of owners. The stock count is calculated for the year 2019, utilising a protection duration of 25 years as the cumulative time interval. The histogram on the horizontal and vertical axes illustrates the distribution density of values for both the x and y axes, respectively. The plot is divided into four equal parts by a vertical line originating from the middle of the x-axis and a horizontal line originating from the middle of the y-axis. This division allows for clear observation of the intensity levels of designs and design owners across different countries.

From Figure 2.15, it becomes evident that a few countries possess the majority of designs globally. Consequently, the majority of scatter plots are concentrated in the lower region of the plot. Moreover, countries with a high intensity of design owners also tend to exhibit a high intensity of designs, resulting in the absence of scatter plots in the lower right portion of the plot. While a few countries may have a small number of design owners but a high intensity of design ownership, this does not necessarily lead to a high value of design count per owner. The higher values of design count per owner are predominantly located in the lower left region of the plot, indicating a low level of both design intensity and owner intensity.

2.5.3.3 Different Types of Designs in Owner Countries

The variation of design registrations across different Locarno classes and owner countries has been a subject of discussion. To visualise the intersectional distribution of industrial designs in these categories, a heatmap can be utilised. The horizontal and vertical axes of the heatmap can represent Locarno classes or countries, while the colours within the heatmap correspond to the design count values. This approach enables the visualisation of the distribution of designs across different countries and Locarno classes.

By calculating the cumulative number of designs from 1854 to 2019 for each Locarno class and owner country, the resulting values can be filled into the heatmap depicted in Figure 2.16. In this heatmap, the vertical axis represents 33 Locarno classes at the 2-digit level, while the horizontal axis represents different owner countries. The cells within the heatmap are filled with colours ranging from light to dark, indicating the number of designs from low to high. It is important to note that the discrete categories on both the x and y axes are sorted alphabetically, rather than based on their total design count.

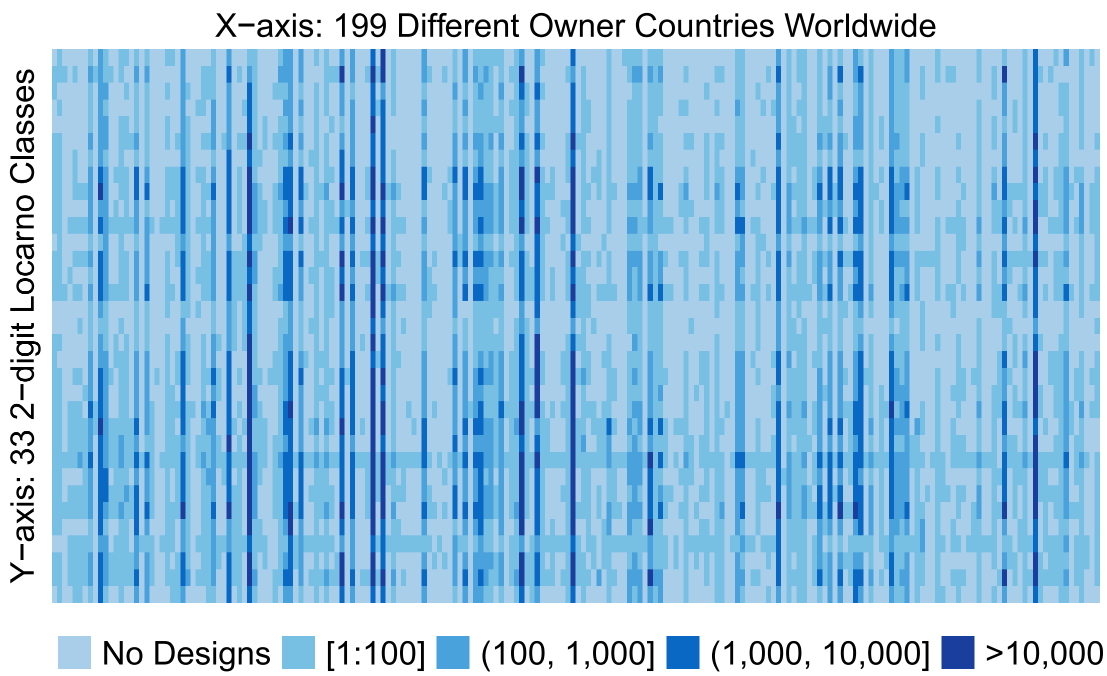


Figure 2.16: Heatmap - Distribution of Designs in Locarno Classes and Owner Countries (1854-2019)

Figure 2.16 unveils prominent vertical bars in dark colours, signifying the dominance of owner countries in the global registration of industrial designs. This finding suggests that the registration pattern is driven primarily by the country of origin rather than the specific design types. Conversely, the intermittent light-coloured horizontal bars indicate that Locarno classes play a pivotal role in determining the prevalence or scarcity of design registrations. This observation implies that certain design types attract limited interest for registration across all countries worldwide.

Nevertheless, the heatmap with alphabetical sequencing on both the x and y axes fails to effectively display the density distribution of values. To identify whether designs were registered by a small number of countries in specific categories, the axes can be reordered based on the total design values within each category. Figure 2.17 presents the same data as Figure 2.16, with only the sequence of the vertical and horizontal axes changed.

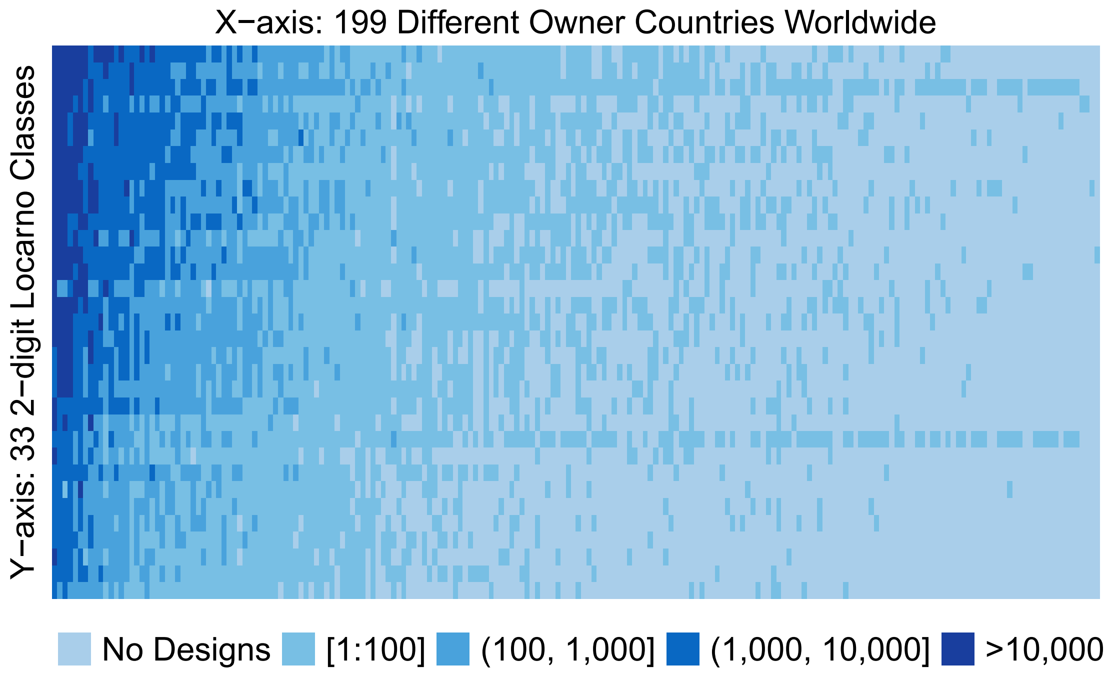


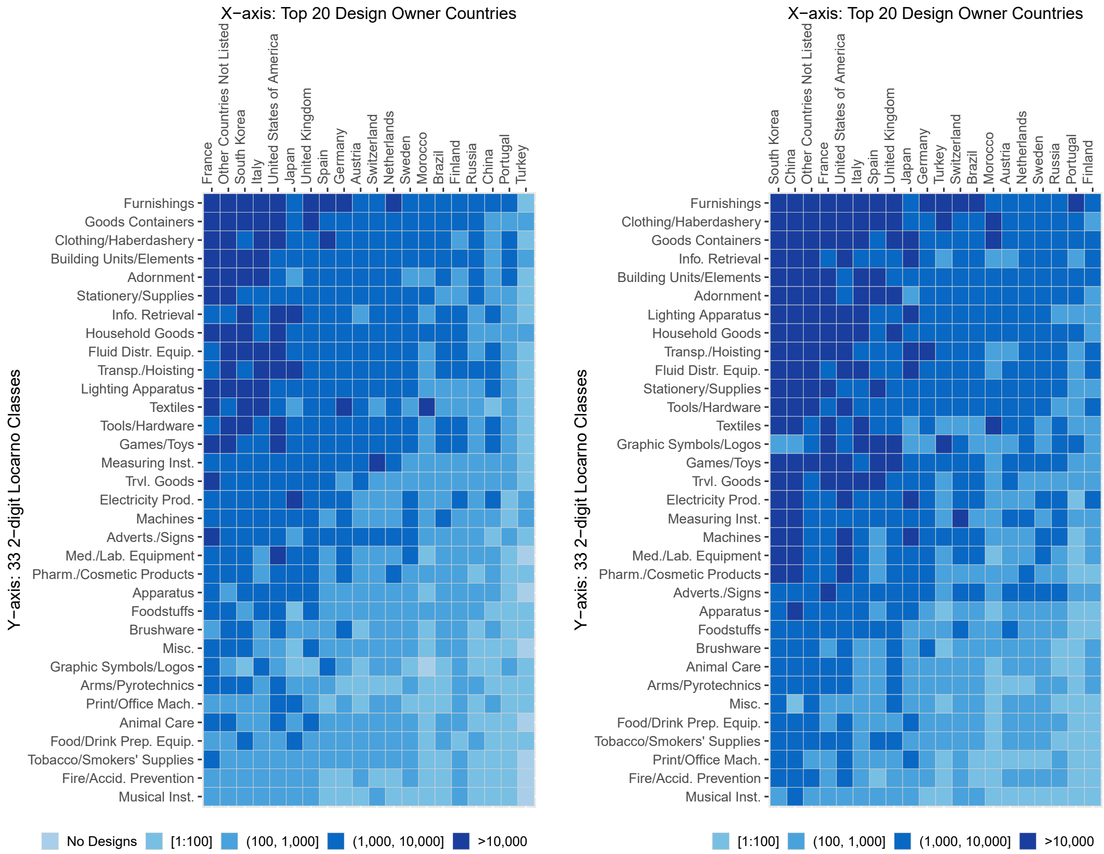
Figure 2.17: Heatmap - Distribution of Designs in Locarno Classes and Owner Countries (1854-2019) (Reordered Axes by Values)

In Figure 2.17, the colour blocks that are surrounded by similar colours make it difficult to discern whether the dominance lies with the categories on the vertical or horizontal axis. However, this arrangement effectively illustrates the distribution of values, indicating that industrial design is predominantly owned by a select few countries across all Locarno classes. Furthermore, the distribution of design counts by Locarno classes and owner countries exhibits a positive skew.

While Figure 2.16 and Figure 2.17 provide an overview of the distribution and trend of industrial design, the horizontal axis, consisting of 199 countries, presents challenges in listing and further analysis of individual countries. Given the argument that industrial design is dominated by the owner country, it is advisable to select the top owner countries as a sample for visualisation in the heatmap.

Figure 2.18a presents a heatmap that showcases the distribution of designs in 2009 among the top 19 owner countries and 33 Locarno classes. The remaining countries are considered as a single entity, resulting in a total of 20 entities included in this heatmap. The x-axis represents the owner countries, while the y-axis represents the Locarno classes. The colours within the heatmap vary from light to dark, indicating the cumulative number of designs registered over the past 25 years for the given year (2009). Dark-coloured cells in the heatmap indicate a substantial number of designs associated with the respective owner countries and Locarno classes.

For comparison, a similar heatmap is plotted for 2019 (see Figure 2.18b), using the same plotting logic and calculation method. A notable observation from 2009 to 2019 is the rise in popularity of designs related to information retrieval, as it becomes one of the most sought-after design categories in 2019, while ranking lower in 2009. This finding aligns with the earlier discussion that this Locarno class holds a central position in the related design network (see Figure 2.6), resulting in a significant increase in registrations from 2009 to 2019.



(a) 2009 (b) 2019

Figure 2.18: Heatmap - Design Distribution in Locarno Classes and Top Owner Countries (Colours Filled in Cumulative Count)

Furthermore, a significant change observed from 2009 to 2019 is the disappearance of cells with no designs, indicating an overall increase in the coverage of primary design owner countries across Locarno classes. Moreover, the colours of the blocks in the heatmap are considerably darker in 2019 compared to 2009, providing clear evidence of the overall growth in design coverage. However, the major owner countries of industrial design exhibit only slight changes in their ranking positions, with an increase in the total number of designs owned by these countries.

The top owner countries do not demonstrate a distinct preference for specific design categories. This suggests that countries with a high concentration of designs aim to cover a wide range of design types, while also producing a larger quantity of popular design types. Nevertheless, when considering designs related to graphic symbols or logos, it is evident that European countries such as France, the United Kingdom, and Spain have made more significant advancements in this category compared to Asian countries including South Korea, China, and Japan.

2.5.4 Target Markets of Industrial Design

The preceding analysis has discussed the registration of industrial designs under the Locarno classes and the countries in which design holders are located. However, it has not delved into the examination of target markets for industrial design. The target market of an industrial design refers to the specific countries in which design owners choose to protect their designs. Due to the territorial nature of industrial design, it is not possible to protect designs worldwide. Instead, if designated for protection in specific countries, they can enjoy protection in multiple jurisdictions. The country in which the design is designated for protection is identified as the target market of industrial design, irrespective of the owner's country or the Locarno classes to which the design belongs.

The dataset contains the earliest design record from 1805, and thus the cumulative number of designs is calculated from 1805 until 2019, representing the latest and most comprehensive coverage of design data. Figure 2.19 visually displays this cumulative count, with countries shaded in colours ranging from light to dark, indicating the increasing number of registered designs from low to high. Notably, China emerges as the most prominent target market, with a disproportionately higher number of registered patents compared to any other country. Additionally, Europe represents another significant market for industrial design, as evidenced by the considerably darker shading assigned to European countries in Figure 2.19.

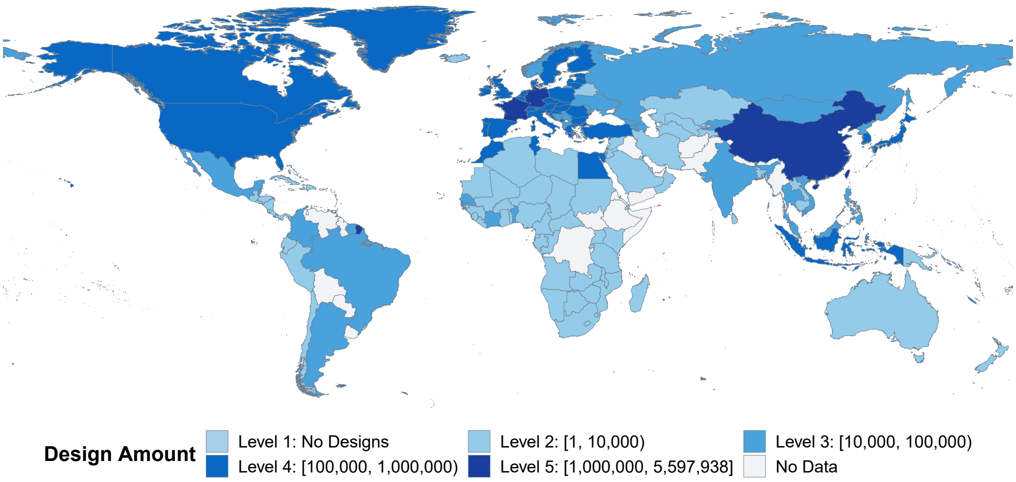


Figure 2.19: World Map - Cumulative Number of Design Registrations in Global Countries (1805-2019)

Given that the cross-sectional representation of designs on the polygonal world map fails to capture the temporal evolution of countries' popularity in the realm of industrial design, an alternative approach employing an area chart is adopted. In this context, the ten most popular target markets (countries) for industrial design worldwide are selected, and the area colours are filled in a gradient from dark to light, reflecting the respective market shares from low to high. The time period under consideration spans from 1990 to 2019. Due to the relatively nascent state of design registration in earlier years, this area chart omits data from those periods. The number of design registrations is computed based on the annual flow of industrial design registrations.

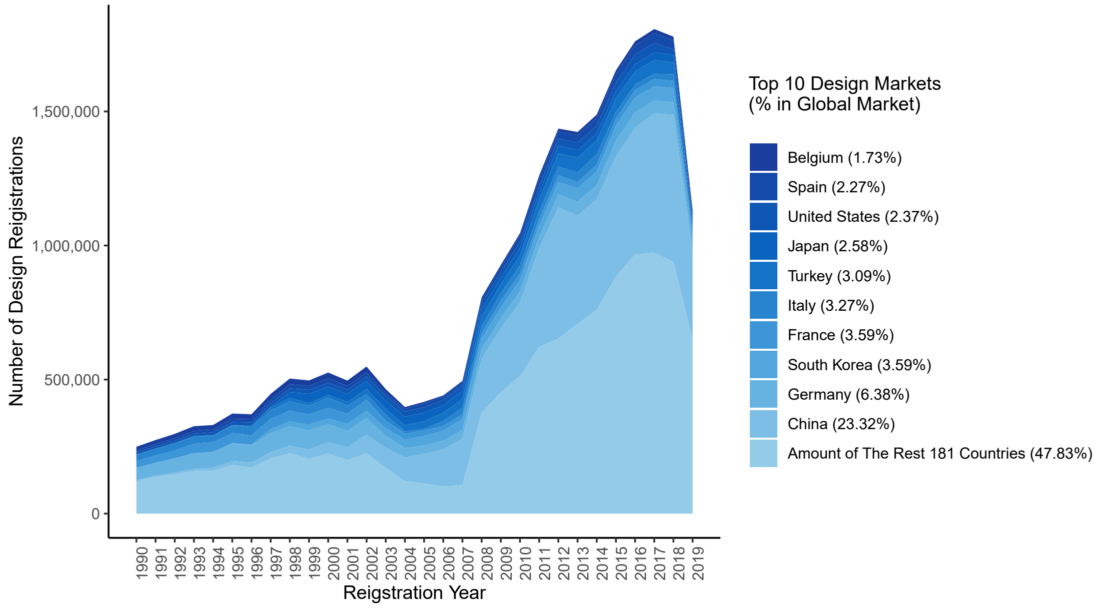


Figure 2.20: Area Chart - Design Registration in Top 10 Global Markets (Time Trend during 1990-2019)

Based on the findings depicted in Figure 2.20, the global registration of industrial design has exhibited a substantial upward trend from 1990 to 2019. Notably, starting from 2017, there has been a rapid increase in the number of design registrations. Additionally, the figure includes a representation of the collective design registrations in the remaining countries, as the top ten markets are selected as a sample. It is evident that these top ten markets account for over 50% of the total global designs, surpassing the number of design registrations in the rest of the countries.

Furthermore, an analysis of historical data spanning from 1990 to 2019 reveals that China not only holds the position as the largest market for industrial design registration but also accounts for over one-fifth of global design registrations. Germany follows as the second largest market, with a significantly higher number of design registrations compared to other popular markets. However, due to limitations in the area chart, it does not effectively present the rankings of global markets, hindering the analysis of their changes over time. Consequently, a bump chart is introduced to facilitate an examination of these rankings.

The bump chart is computed based on the cumulative number of design registrations within specific markets over ten-year periods. By selecting countries that consistently rank within the top ten in both earlier and later time periods, their respective changes in rankings are compared in the bump chart. Dark colours are assigned to countries that have risen in rankings, while middle-shade colours represent countries that have maintained their rankings, and light colours indicate countries that have experienced a decline in rankings.

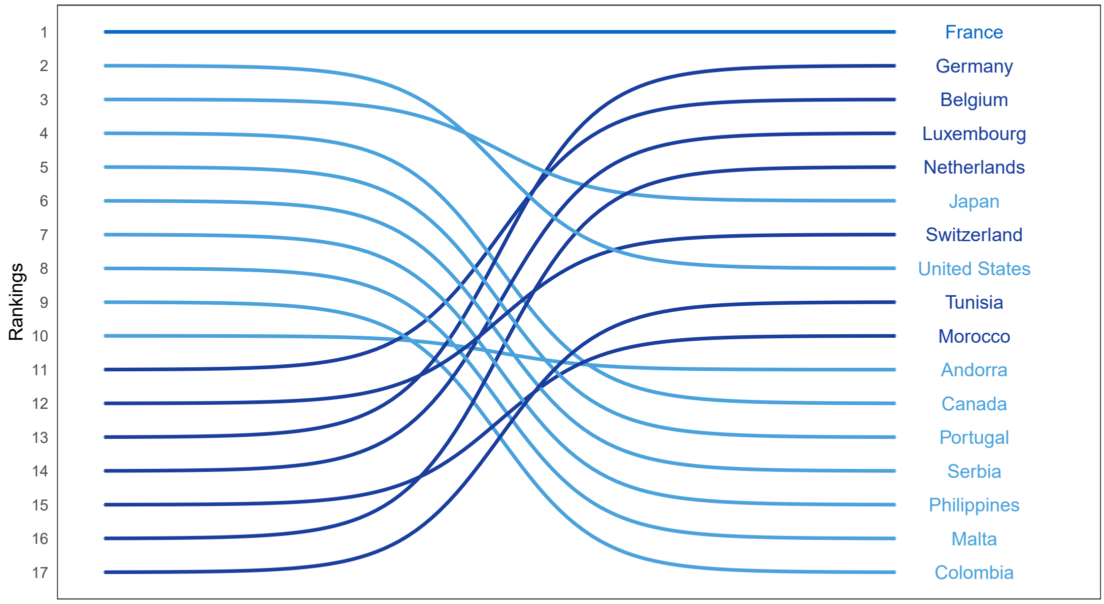


Figure 2.21: Bump Chart - Comparison of Market Rankings (1950-1959 vs 1980-1989)

The bump chart (see Figure 2.21) provides a comparison of the rankings of the most popular design markets during the time periods of 1950-1959 and 1980-1989. It is evident that France held the top position as the most registered design market during the early years from 1950 to 1989. Other European countries, including Germany, the Benelux countries (Belgium, the Netherlands, and Luxembourg), and Switzerland, experienced an upward shift in their rankings from 1950-1959 to 1980-1989. Conversely, the rankings of Japan and the United States declined during this period, indicating a decrease in their relative popularity compared to the earlier years. Notably, China did not emerge as one of the most registered countries for industrial design during the specified time period.

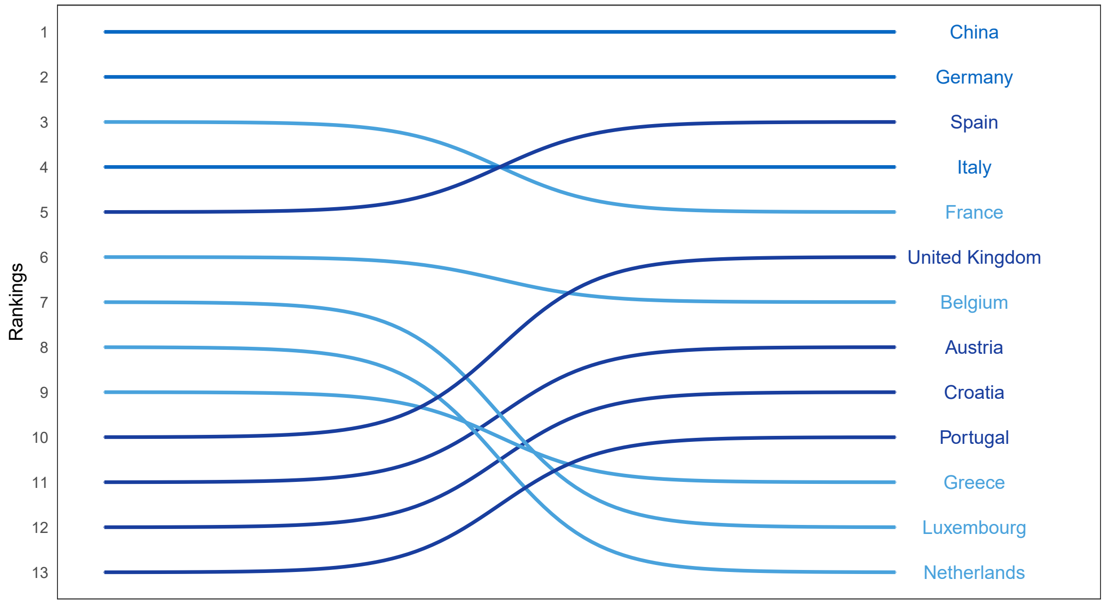


Figure 2.22: Bump Chart - Comparison of Market Rankings (1990-2009 vs 2010-2019)

The comparison of rankings among design markets within the periods of 1990-2009 and 2010-2019 is illustrated in Figure 2.22. A notable observation is that the rankings appear relatively stable in the latter figure, indicating a trend towards unchanged popularity in the design markets.

To summarise, the attractiveness of various design markets has undergone significant changes from earlier years to more recent times. Based on the cumulative number of design registrations across all historical data, the most popular markets include China, Germany, South Korea, Japan, and European countries. It is important to note that designs registered with EUIPO are protected throughout all European countries, making the European market a commonly investigated entity.

However, it is also possible for owners of industrial designs to register their work in specific European countries, designating protection solely within those jurisdictions rather than across the entire continent. Additionally, it is worth highlighting that design registration can occur internationally, allowing owners to register their designs not only in their home countries but also in foreign countries. Consequently, the ownership structure of designs in a given market is complex, warranting an analysis of cross-border design registrations.

2.5.4.1 Cross-border Design Registration

When registering industrial designs, if the design owners designate a foreign country different from their own as the territory for design protection, it is categorised as cross-border registration. Conversely, designs where the owner country and protection country are the same are considered national registrations. The number of cross-border design registrations and national design registrations can be calculated for each year. Furthermore, by dividing these numbers by the total number of design registrations in each year, the proportions of national and cross-border registrations can be computed. These proportions can be effectively presented using a stacked bar chart.

The stacked bar chart in Figure 2.23 illustrates the time-varying proportions of cross-border and national design registrations. The calculations are based on the count of valid designs for each year, taking into account the 25-year protection duration.

Specifically, the count of designs in a given protection territory in a certain year is the cumulative number of designs from the past 25 years, including the current year. The time period covered in this figure spans from 1950 to 2019. As depicted in the figure, there is a notable upward trend in the proportion of cross-border design registrations, while the proportion of national design registrations experiences a significant decline.

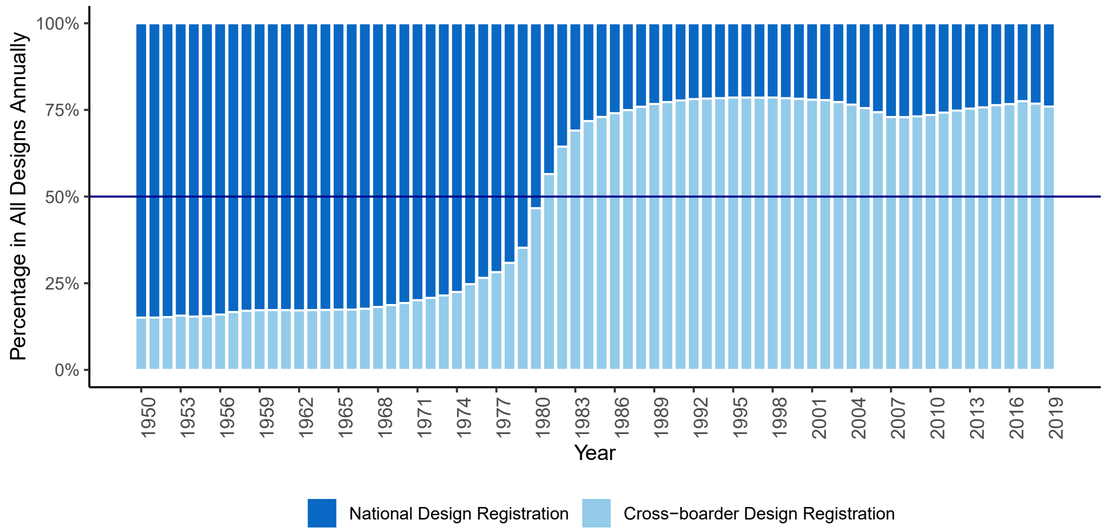
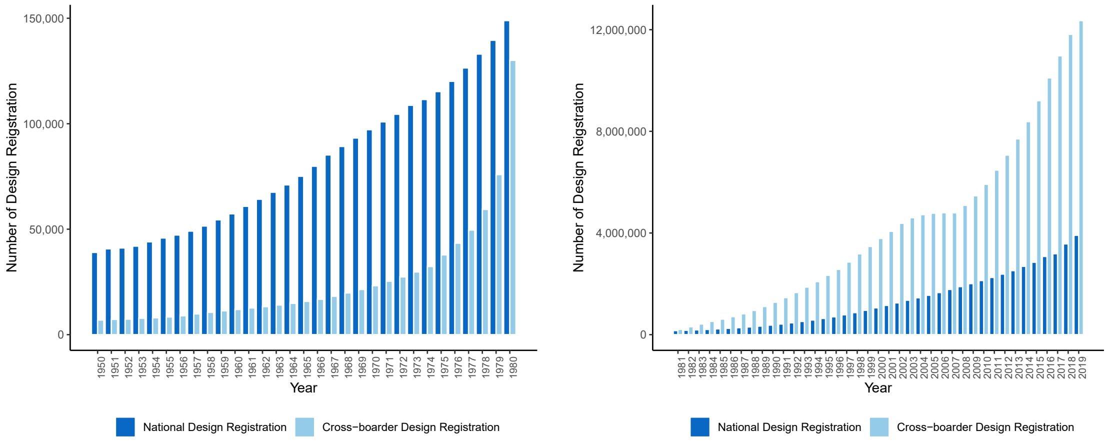


Figure 2.23: Bar Chart - Proportion of National and Cross-border Design Registration

In more detail, the proportion of cross-border design registrations exhibits a gradual increase in the early years, followed by an acceleration in the rate of increase. However, this rate of increase reaches a plateau after 1983. In recent years, both the proportions of cross-border and national design registrations demonstrate a stable pattern, indicating a steady structure of design registrations in the global market. Furthermore, in the early years, although cross-border design registrations experienced rapid growth, national design registrations remained predominant worldwide. However, starting from 1981, the proportion of cross-border design registrations surpasses that of national design registrations, signifying a shift in the global design registration landscape.

Nevertheless, the changes in the number of design registrations cannot be adequately represented solely through the stacked bar chart depicting proportions. To comprehensively assess the extent of changes in both types of design registrations over time, a grouped bar chart is employed. This chart displays the number of design registrations for both cross-border and national categories side by side for each time point. The cross-border design registrations are depicted in a lighter colour, while the national design registrations are represented in a darker shade.

As discussed earlier, the year 1981 marks a turning point, as the number of cross-border design registrations surpasses that of national design registrations. Consequently, the grouped bar chart is divided into two sub-figures, illustrating the trends from 1950 to 1980 and from 1981 to 2019, respectively. These sub-figures are presented in Figure 2.24.



(a) 1950-1980 (b) 1981-2019

Figure 2.24: Bar Chart - National and Cross-border Design Registration (1950-2019)

Figure 2.24a illustrates the temporal evolution of the number of cross-border design registrations and national design registrations within the 1950-1980 period. This figure predominantly displays a dark colour, indicating the prevalence of national design registrations during this timeframe. However, a noticeable surge in cross-border design registrations is observed in 1980, where the number of cross-border design registrations becomes approximately equal to that of national design registrations.

Furthermore, Figure 2.24b showcases the number of national design registrations and cross-border design registrations from 1981 to 2019. The overall lighter colour suggests that cross-border design registrations have surpassed national design registrations during this period. Moreover, three distinct stages of cross-border design registration growth can be discerned. The first stage spans from 1981 to 2002, characterised by a rapid and escalating increase in cross-border designs. The second stage, occurring from 2003 to 2007, demonstrates a plateau in cross-border design registrations, with no apparent upward or downward trend. Lastly, from 2008 to 2019, the third stage showcases a renewed surge in cross-border design registrations, characterised by an exceptionally high growth rate.

Additionally, when examining cross-border designs, it becomes evident that European countries possess a substantial proportion. Considering the popularity of the European market as a target for industrial design, it is essential to conduct a specific investigation into cross-border designs within European countries. From this point onwards, cross-border designs can be further categorised into four groups: designs registered in the European market and owned by European countries, designs registered in the European market and owned by non-European countries, designs registered in non-European countries and owned by European countries, and designs registered in non-European countries and owned by non-European countries.

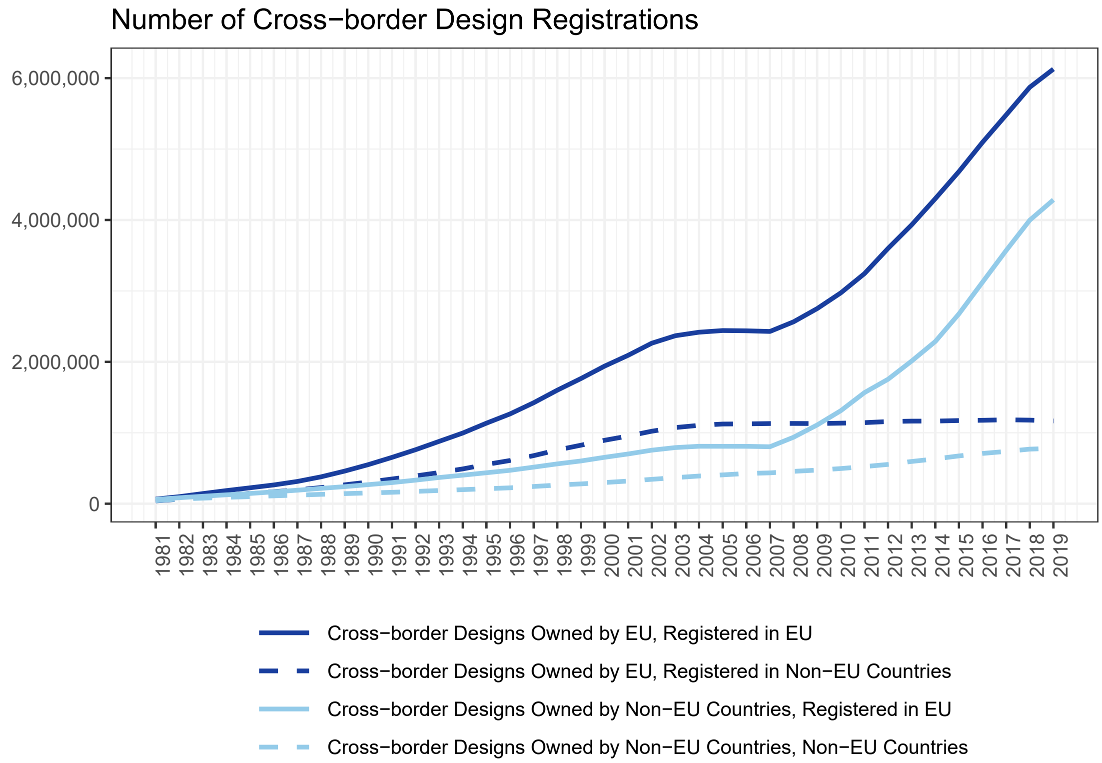


Figure 2.25: Line Chart - Comparison of EU and Non-EU Cross-border Designs

Given the breakthrough point of cross-border designs in 1981, the investigation focuses on the period from 1981 to the most recent year in the dataset, which is 2019. Figure 2.25 presents line types based on the target market of industrial design. The dashed line represents designs registered outside of European countries, while the solid line indicates designs protected within European countries. Colours are assigned according to the owner countries, with light colours denoting designs owned by non-European countries and dark colours representing designs owned by European countries. The line chart showcases four distinct groups based on the combination of line type and colour.

Figure 2.25 reveals that prior to 2009, European owners dominated cross-border design registrations. The figure demonstrates that, before 2009, the number of designs owned by European countries, regardless of their protection location, exceeded the number of other types of cross-border designs. Moreover, after 2009, cross-border designs owned by non-European countries but registered in Europe experienced a rapid increase, surpassing the quantity of cross-border designs owned by European countries and registered in non-European countries.

It can be argued that the analysis of cross-border design registrations cannot be dissociated from EU or non-EU design registrations. Therefore, it is necessary to discuss this analysis in two distinct time stages. In the early stage from 1981 to 2009, European owners dominated cross-border designs, as evidenced by the higher number of cross-border designs compared to other types. The second stage begins in 2009, during which cross-border design registrations are predominantly driven by the European market as the territory of protection. As depicted in Figure 2.25, after 2009, the number of designs designated to European countries is significantly higher than other types.

2.5.4.2 Distribution of Cross-border Designs in Locarno Classes

In the context of protecting industrial design, it has been noted that registration can be sought in a foreign country apart from the country of origin. Owners may have distinct preferences when selecting the jurisdiction for protecting different types of industrial design. By categorising design registrations into two groups - national and cross-border registrations - we can analyse the distribution across various Locarno classes within each group. To visualise this distribution, a radar chart can be utilised. The total number of design registrations represents 100% of the dataset, and the proportions of cross-border and national registrations can be calculated accordingly.

To begin, the dataset can be divided into two groups based on the owner's country and the protection territory of the industrial design. The number of designs in each group can be determined. Considering the total number of designs as 100%, each group's designs can be plotted on a radar chart to observe their distribution across different Locarno classes at the 2-digit level. For the purposes of this analysis, we will focus on the year 2019 as a snapshot in time, assuming a protection duration of 25 years. This will allow us to calculate the cumulative count of valid designs in different Locarno classes for both cross-border and national registrations. The resulting radar chart is presented in Figure 2.26.

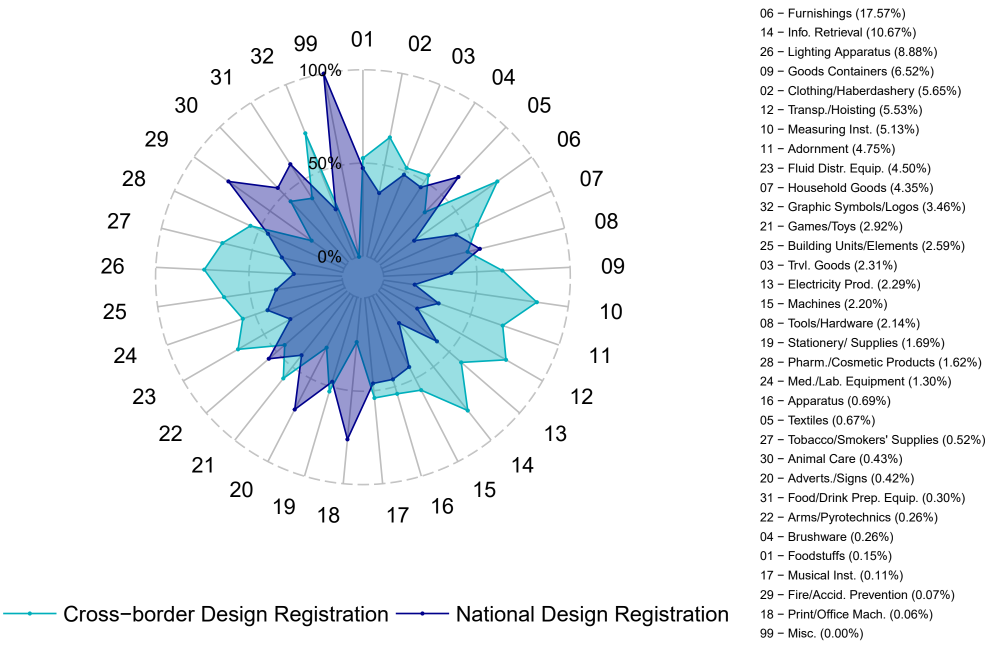


Figure 2.26: Radar Chart - Comparison of Design Distribution in Locarno classes between Cross-border and National Registrations (2019)

Figure 2.26 illustrates the variations in Locarno classes for designs registered either locally or in foreign countries. Notably, the radar chart shows a distinct pattern, with cross-border design registrations depicted in a lighter shade and national design registrations in a darker shade. The light-coloured area significantly overlaps with the dark-coloured radar area, indicating a comprehensive prevalence of cross-border designs across all Locarno classes.

Moreover, a significant proportion of the world's registered designs pertain to furnishing, with over 50% of these designs being registered in foreign countries rather than the owner's country of origin. Similarly, a majority of designs in the categories of information retrieval, electricity products, transport goods, lighting apparatus, and measuring instruments are registered cross-border. Conversely, designs for print machines and advertising signs are predominantly registered locally rather than internationally.

Based on the aforementioned analysis, it is evident that a substantial number of cross-border designs are registered in the European market. This suggests a dominance of the European market in terms of cross-border design registrations, warranting further investigation. Consequently, cross-border designs registered in European markets can be categorised based on the ownership countries, distinguishing between designs owned by European countries and those owned by non-European countries.

Figure 2.27 presents the division of cross-border designs registered in Europe into two groups: designs owned by European countries (depicted in light colour) and designs owned by non-European countries (depicted in dark colour). The number of designs in each Locarno class is calculated based on the cumulative design count in 2019, assuming a protection duration of 25 years.

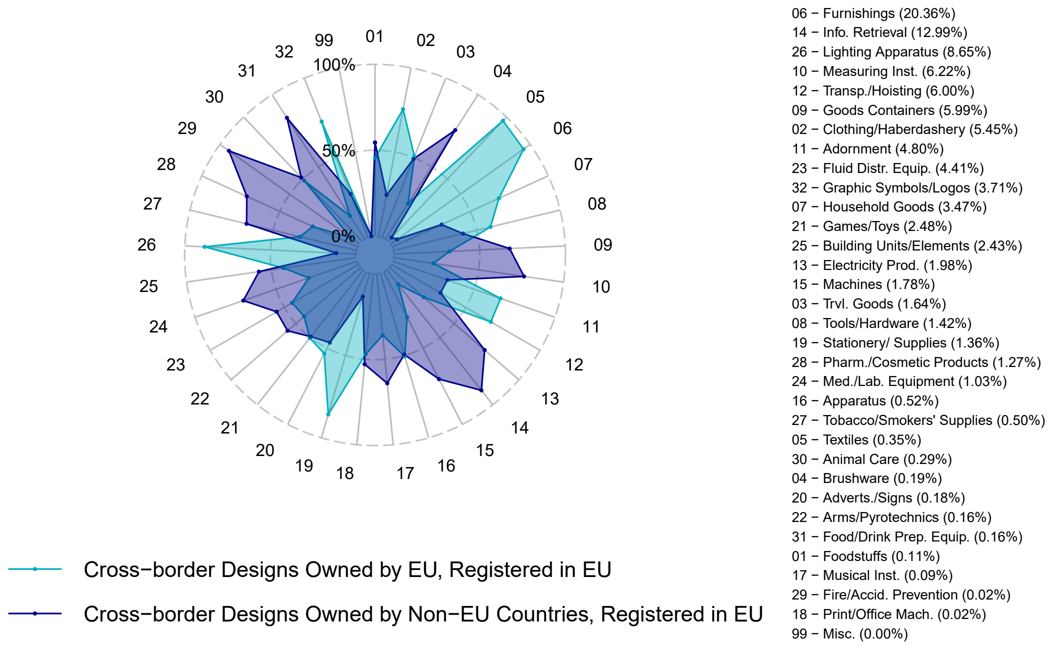


Figure 2.27: Radar Chart - Locarno Distribution of EU Reigstered Cross-border Designs (EU Owners vs Non-EU Owners in 2019)

Based on the findings depicted in Figure 2.27, it is evident that the most popular cross-border designs registered in Europe align with the designs that are most commonly registered worldwide. This suggests that, in terms of design distribution across Locarno classes, cross-border designs exhibit consistency between the global and European markets. Furthermore, the cross-border designs registered in the European market display a well-defined categorisation, with no miscellaneous designs observed.

Notably, nearly all cross-border designs registered for furnishing and textiles in Europe are owned by European countries. Similarly, a majority of cross-border designs registered in Europe for clothing, lighting apparatus, logos, adormants, transport, and stationery are also owned by European entities. In contrast, a significant proportion of cross-border designs registered in Europe for information retrieval, measuring instruments, and fire prevention, among others, are owned by non-European countries.

Moreover, in addition to investigating cross-border designs registered in the European market, it is essential to explore another subset of cross-border designs - specifically, those registered in non-European countries. Similar to the categorisation approach employed for cross-border designs registered in Europe, the cross-border designs registered in non-European markets can also be divided into two groups based on the ownership countries' European affiliation.

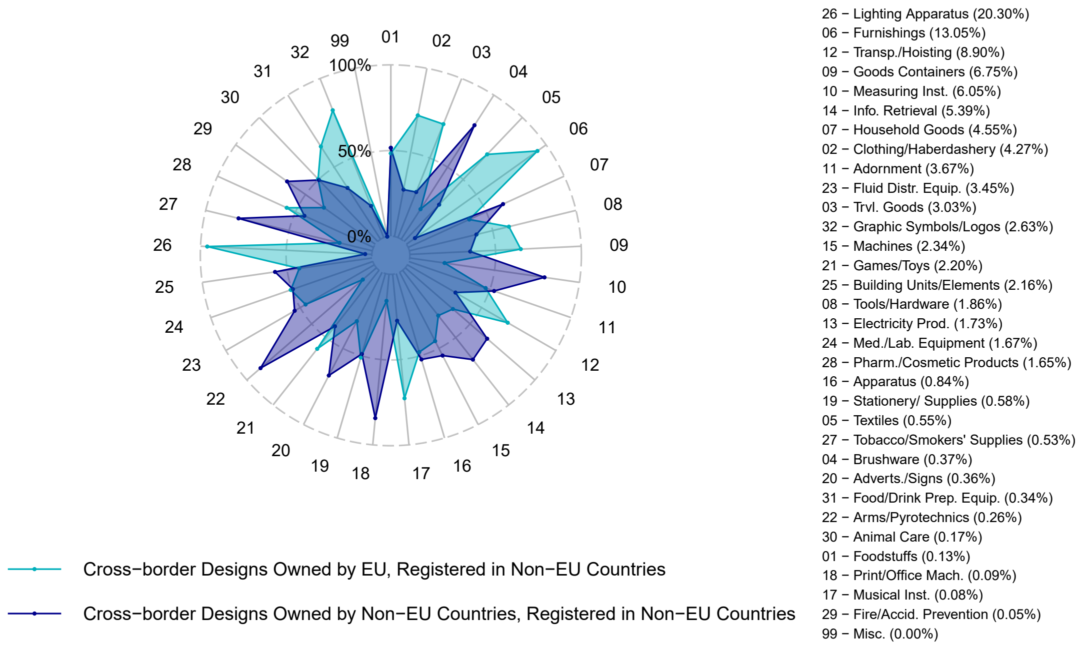


Figure 2.28: Radar Chart - Locarno Distribution of Non-EU Reigstered Cross-border Designs (EU Owners vs Non-EU Owners in 2019)

Figure 2.28 provides a visual representation of the analysis, where the light colour represents cross-border designs registered in non-European countries and owned by European countries. Conversely, the dark colour represents cross-border designs registered in non-European countries but owned by European countries. The cumulative count of designs for each Locarno class is calculated for the year 2019, assuming a protection duration of 25 years.

Examining Figure 2.28, we observe that the most frequently registered designs in non-European countries pertain to lighting apparatus, which differs from both the global and European markets. This suggests that, to some extent, the European market dominates the cross-border designs in the global design market. Notably, nearly all cross-border furnishing designs registered in non-European countries are owned by European countries, indicating that European countries are the primary owners of furnishing designs.

Furthermore, cross-border designs for pharmaceutical and cosmetic products, as well as designs for arms and pyrotechnics, registered in non-European countries are predominantly owned by non-European countries. In contrast, there is no significant difference in terms of ownership countries for these designs registered in European countries.

2.6 Discussion

Utilising data visualisation as a method to explore global industrial design reveals its evolution across historical and ongoing industry revolutions. Moreover, industrial design exhibits distinctive distribution across different Locarno classes, signifying variations in design objects. High-tech products hold a central position in the design network. Additionally, industrial design appears to be predominantly influenced by owner countries and target markets rather than its objects. Based on these findings, this discussion section aims to provide a comprehensive understanding and explanation of industrial design from multiple perspectives.

2.6.1 Evolution of Industrial Design

Analysing the timeline of historical design data reveals a close connection between the development of industrial design and industry revolutions. From Industry 1.0 to Industry 4.0, and the emerging Industry 5.0, defined as a societal value-driven industrial revolution beyond economic growth (X. Xu et al., 2021), manufacturing industries have undergone significant transformations. Concurrently, industrial design has transitioned from an emerging stage to a current booming stage. The relationship between the development of industrial design and industry revolutions can be explained from several perspectives.

Firstly, industry revolutions introduce new technologies (M. Xu et al., 2018), which is a core driver behind the rapid evolution of industrial design. Improved manufacturing processes resulting from industry revolutions lead to increased competition (Antunes et al., 2018). Business competitiveness can be assessed based on two aspects: meeting or leading market demands (Hassan, 2000) and surpassing competitors in terms of productivity (Carayannis and Grigoroudis, 2014). Product differentiation through appropriate design satisfies market demand from various aspects, including cultural value and functional requirements (Johnson and Myatt, 2006), while well-planned mass production via industrial design enhances productivity (Rusten and Bryson, 2007).

Secondly, the abundance of goods resulting from industrial revolutions has expanded consumer choices and demands (Manda and Ben Dhaou, 2019; Mokyr, 2005). After the industrial revolution, goods became widely and sufficiently available to consumers (Lucas, 2002), prompting consumers to seek products that align with their lifestyle and taste. This drives the development of industrial design, as well-designed products become the optimal choice for consumers (Neha and Aravendan, 2023). Furthermore, market preferences tend to favour products with societal values and aspirations (Ceschin and Gaziulusoy, 2016). Industrial design plays a pivotal role in reflecting consumers' personal social status and identity through product design.

Lastly, industry revolutions have facilitated global connectivity through advancements in transportation and communication technologies (Adeniran, 2016). This enables people from different places to gather, accelerating the exchange of novel ideas and creative work (Andersson et al., 2016; Deichmann et al., 2020). Industrial design, as a creative endeavour highly reliant on idea exchange, benefits from improved global connectivity. In summary, the Industrial Revolution created a fertile ground for the emergence of industrial design by fostering technological advancements, changing consumer demands, evolving societal values, and facilitating the exchange of design knowledge.

2.6.2 Drivers of Industrial Design

In addition to the evolution of industrial design over time, this section aims to explore the extent to which industrial design is driven by owner countries, target markets, and design objects. As discussed in Section 2.5.2, designs are intensive in furnishing, packaging, and clothing sectors, while the core design that connects other types pertains to information retrieval and medical or lab equipment, which involve advanced technologies. Furthermore, compared to technology-driven industrial design, different economies as design owner countries and target markets dominate the global distribution of industrial design. Technologies, ownership countries, and target markets as drivers of industrial design can be discussed separately.

Firstly, industrial design is driven by technologies, consistent with the finding that industrial design develops alongside industry revolutions. During each industrial revolution, there is significant technological improvement, leading to substantial progress in industrial design. Existing research also supports the notion that technology serves as a key driver of innovation (Bottomley, 2014; Taalbi, 2017), enhancing an economy's innovation capabilities. Industrial design, as part of the innovation landscape, benefits from this technological progress alongside other types of innovation.

On the other hand, industrial design is significantly influenced by economies, both as ownership countries and target markets. The global distribution of industrial design is heavily concentrated in several countries, rather than being evenly spread across the world. Different countries possess varying innovation capabilities (H. Lu et al., 2022), which can be further investigated from the perspective of innovation capability. Moreover, target markets dominate the distribution of industrial design worldwide. Design registration is driven by commercial considerations, with patenting behaviour considering market potential and economy size (Jaffe, 1986).

Additionally, this study reveals the number of cross-border design registrations at the country level, serving as an indicator of market scale and design capability in terms of industrial design. In this case, a country's development level of industrial design is associated with economy size and innovation degree. Countries with a high number of registered designs are likely to have a more developed and innovative industrial sector (Gerlitz, 2015), contributing to overall economic growth and competitiveness in the global market.

2.6.3 Global Connectedness in Industrial Design

As discussed in Section 2.5.4.1, a significant proportion of global designs are cross-border registered, with this trend increasing over time. Moreover, cross-border design registration is particularly prevalent in European countries. Cross-border registered industrial design exhibits a pattern similar to trade, where designs can be registered in a different country from the owner's home country. Furthermore, European design registration indicates the dominance of the European market in cross-border design registrations. Additionally, geographic proximity attracts different European countries to own European community designs. The global connectedness in industrial design can be understood from the following perspectives.

Firstly, industrial design is intellectual property that protects designs from infringement. When entering foreign markets, design owners can obtain legal protection through cross-border design registration (WIPO, 2006). This aligns with the motives behind patenting activities, as design holders seek legal protection for their products before conducting business (Wunsch-Vincent et al., 2015).

Moreover, industrial design provides owner firms with a comparative advantage in the global market (Fujimoto, 2008; Katz, 1984), particularly when owners register designs in foreign markets. Protecting unique aesthetics is the primary objective of industrial design as intellectual property, safeguarding both functionality and societal value. This enables businesses to differentiate their products from others and gain a foothold in foreign markets.

Lastly, cross-border design registrations tend to occur more frequently between countries with higher levels of geographic, physical, or political connectedness. European countries, for instance, are more likely to register designs within the European market, while the European market itself serves as a primary hub for industrial design. This underscores the significance of European countries in the global industrial design network, necessitating that businesses expanding into the global market consider the European market as a key target for their industrial design strategies.

In conclusion, industrial design plays a crucial role in the global economy and is closely intertwined with international trade. Cross-border design registration enables businesses to protect their intellectual property and gain a competitive advantage in foreign markets. The number of registered designs at the country level serves as an indicator of a country's level of development in terms of industrial design. The prominence of the European market in industrial design underscores its importance as a key target market for businesses aiming to expand globally.

2.7 Conclusion

This paper has utilised data visualisation to explore the evolution of global industrial design and its drivers. The analysis has revealed a close connection between the development of industrial design and industry revolutions, with new technologies playing a crucial role in driving its evolution. The abundance of goods resulting from these revolutions has expanded consumer choices and demands, leading to the development of industrial design as a means to satisfy consumer preferences and reflect societal values. Furthermore, the global connectivity facilitated by advancements in transportation and communication technologies has accelerated the exchange of ideas and creative work, enhancing the development of industrial design.

The drivers of industrial design have been identified as technologies, ownership countries, and target markets. Technological advancements have been found to be a key driver, as they enable product differentiation and enhance productivity. Different economies as design owner countries and target markets have a significant influence on the global distribution of industrial design, with certain countries exhibiting higher innovation capabilities and dominating the ownership and market of industrial designs. Cross-border design registrations have also been observed, indicating the importance of protecting intellectual property and gaining a competitive advantage in foreign markets.

The global connectedness in industrial design has been evident through the prevalence of cross-border design registrations, particularly in European countries. This highlights the significance of the European market as a key target for businesses expanding globally. Industrial design serves as a means to protect unique aesthetics, differentiate products, and gain a foothold in foreign markets.

In conclusion, industrial design plays a crucial role in the global economy and is closely intertwined with international trade. The evolution of industrial design is driven by industry revolutions, consumer demands, and technological advancements. The concentration of industrial design in certain countries and its prevalence in cross-border registrations emphasise the importance of ownership countries and target markets. The European market, in particular, stands out as a hub for industrial design. Understanding the dynamics and drivers of industrial design is essential for businesses aiming to expand globally and succeed in an increasingly connected world.

Chapter 3

Unleashing the Power of Industrial Design: A Catalyst for Export Growth

3.1 Introduction

Industrial design encompasses the entire process from product development to mass production and final marketing strategies. It involves various innovative activities such as research and development, product optimisation, marketing, and enhancing user experiences (Heskett, 1980, 2003, 2017; Verganti, 2009; Verganti and Öberg, 2013). In essence, industrial design acts as a bridge, connecting user experiences with the core technologies of products. From a legal standpoint, industrial design, also referred to as design patent, represents a type of patent that protects the visual appearance of articles, serving as innovation outputs and intellectual properties to be safeguarded (WIPO, 2006). It complements traditional patents, which primarily protect solely functional technologies.

The comprehensive enhancement of commodities through industrial design leads to increased attractiveness, market share, and overall market competitiveness of products and firms (D'Ippolito, 2014; Walsh, 1992). Furthermore, legal protection of industrial design grants owner firms a comparative advantage in the global market. Competitiveness derived from innovation and intangible assets has been identified as a key determinant for firms to maintain a favourable position in Global Value Chains (GVCs) (Tsakanikas et al., 2022). Additionally, exports, as the final stage of production in GVCs, serve as a measure of countries' involvement in GVCs. Therefore, exploring the relationship between industrial design and exports can shed light on the extent to which countries can benefit from industrial design within GVCs.

To investigate this relationship, this study utilises global design records data obtained from Questel IP to measure design indicators across different countries. Industrial design is assessed from various perspectives: (i) design capability, indicating the size of industrial design within a country; (ii) design complexity and design relatedness, constructed using the methodology of economic complexity theory proposed by (Hidalgo, Klinger et al., 2007) and its application to patent data (Hidalgo, 2021; Jun et al., 2020);

(iii) design comparative advantage, measured using the methodology of revealed comparative advantage (RCA) (Serin and Civan, 2008); and (iv) design similarity, capturing the structural resemblance of designs between different countries, measured through the similarity indicator proposed by Bahar et al. (2014). Additionally, export values are derived from trade data collected from UN Comtrade. Control variables include regional trade agreements, most favoured country tariff rates, and export similarity, which is measured using a similar logic to design similarity.

The relationship between industrial design and exports is explored using the gravity model (Breschi et al., 2003), a widely employed framework for studying the determinants of trade. Pseudo-Poisson Maximum Likelihood is employed as the statistical technique to estimate correlation coefficients and assess statistical significance. The study's findings suggest that industrial design plays a promoting role in exports. Specifically, design capability, design comparative advantage, and design relatedness have a direct positive effect on exports. Design similarity moderates exports by influencing the impact of design capability and design relatedness. Moreover, design complexity enhances exports by amplifying the design comparative advantage, while also potentially intensifying the negative effect of export similarity on export value.

3.2 Hypothesis Development

The concept of the intangible economy was introduced by Stiglitz and Greenwald (2014) in their book *Creating a Learning Society*. The book emphasises the importance of knowledge, innovation, and intellectual property rights as key factors for sustained economic growth. Haskel and Westlake (2018) provide a definition suggesting that the intangible economy comprises industries that produce knowledge-intensive products involving design, branding, artistic work, and research and development activities. Existing research shows that the intangible economy drives productivity growth (Roth and Thum, 2022) and returns to scale (Hand, 2003). Additionally, a high level of intangible assets allows firms to be flexible and enter new markets (Damodaran, 2007). Furthermore, creative sectors or environments lead to high employee satisfaction levels (Mayfield et al., 2020).

The concepts of the intangible economy and knowledge-based economy are not clearly distinct from one another, as both emphasise the production, distribution, and consumption of goods and services based on knowledge-intensive activities (Godin, 2006). In a knowledge-based economy, great importance is placed on knowledge and information as the primary driving factors for economic growth and development (K. H. Smith, n.d.). This economic model prioritises intellectual capital above other forms of capital such as natural resources or physical assets (Powell and Snellman, 2004). Furthermore, the rise of technology, new forms of communication, collaboration, and design are interlinked with the knowledge-based economy (Howells et al., 2012; Kimbell and Perry, 2001). Under this context, the idea of a design economy can be introduced.

The design economy, as a branch of the intangible economy, encompasses the economic impact resulting from the production and consumption of design goods and services, including areas such as advertising (Kao and Du, 2020), graphic design (Bonsu et al., 2020), fashion design (Aspers, 2010), industrial design (Gemsera and Leendersb, 2001), and more. Within the design economy, designers and design sectors across various industries play a crucial role in contributing to both national and global economic growth (Design Council, 2018). The concept of the design economy acknowledges that design is not solely viewed as an artful or aesthetic ability but rather as a propelling force for fostering innovation, expanding businesses, promoting cultural advancement, and enhancing social welfare.

As previously mentioned in the definition of the intangible economy, industrial design is one of the creative activities included in this concept. Industrial design refers to the process of applying design principles and concepts to physical products intended for large-scale manufacturing production (Heskett, 1980). On the other hand, design-driven innovation is user-centered and focuses on applying design knowledge to products based on consumer needs or user experience rather than solely on product functionality (Verganti and Öberg, 2013). By developing innovative offerings tailored to high-growth, high-margin markets, design-driven innovation can set a company's offerings apart from competitors (Verganti, 2009).

In order to seek protection for their industrial designs, creators and owners often choose to register their design outputs as a form of design patent. According to WIPO (15/09/2022), registered designs are legally protected against commercial activities by non-owners or pirates. Thus, design registration provides intangible assets that belong exclusively to the design owner. Commercialising intangibles enables firms and individuals to benefit from their creations (Flignor and Orozco, 2006). As a result, commercialised intellectual outcomes enter the market, driving innovation and growth.

At the firm level, intangible assets such as registered designs play a crucial role in exports (Bryl, 2020; Rodríguez and Rodríguez, 2005), providing SMEs with a competitive advantage (Chen and Chang, 2013). When existing products enter foreign markets, product design is particularly important compared to other forms of innovation (Alvarez and Robertson, 2004). Design-driven innovations play a significant role in enhancing economic development and competitiveness, enabling companies to differentiate their offerings in high-growth, high-margin markets.

Intangible assets provide a measure of innovation performance (Acs et al., 2002; Katila, 2000). Notably, research indicates that innovation performance has a direct impact on export performance and also plays a mediating role in promoting exports (Azar and Ciabuschi, 2017). Product design is particularly relevant for export performance, with evidence suggesting that it directly affects exports (Tsinopoulos et al., 2014). However, design is considered a complex process that happens throughout the entire industry chain (Tjalve, 2015), making it challenging to determine the direct versus indirect effects of design innovation on exports. Therefore, it may be useful to separately consider both perspectives of how design innovation impacts exports, both directly and indirectly.

3.2.1 Direct Effect of Design on Exports

Product adaptation is a common issue faced by export-oriented companies, highlighting the importance of designing products suited for foreign markets (Kacker, 1975). According to the research by Calantone, Tamer-Cavusgil et al. (2004), following product standardisation policies, products can keep original packaging; however, it can result in difficulties adapting to the foreign market. Based on US firm-level data, existing empirical evidence suggests that firms with greater product design capability exhibit higher levels of international product adaptation (Calantone, Tamer-Cavusgil et al., 2004). Design not only facilitates product adaptation but also provides opportunities for differentiation (Filitz et al., 2015). Product differentiation can be achieved through visuals or user experience and can even optimise production costs (Desai et al., 2001). By leveraging design in exports, countries can gain a competitive advantage in the global market.

H1: Design capability of exporting countries positively affects exports.

Design capability is often measured by the amount of design, but this metric may fail to capture a country's comparative advantage in design due to differences in the size of economies. To account for this, we can use the concept and measurement method of revealed comparative advantage (RCA). Serin and Civan (2008) note that RCA is an important indicator of a country's international competitiveness. For instance, Balland, Boschma et al. (2019) applied RCA with patent data to measure technology comparative advantage. Since design patents and regular patents share some similarities, RCA can also be used to capture comparative advantages in design. Thus, following the original concept of revealed comparative advantage, design comparative advantage (DCA) can be understood as a measure of a country's competitiveness in design.

Sener and Delican (2019) posit that innovation has a positive relationship with competitiveness, which in turn promotes international trade. Empirical evidence by Narula and Wakelin (1998) corroborated the importance of technology competitiveness in improving foreign direct investment and international trade. Patents are often used as indicators to measure technology competitiveness. Recent empirical studies have attested that higher levels of competitiveness measured through patents generate greater exports (Bierut and Kuziemska-Pawlak, 2017). In this regard, design comparativeness attributes, which directly measure national competitiveness in terms of design innovation, may be regarded as having a positive association with trade.

H2: Design comparative advantage of exporting countries positively affects export value

In addition to the revealed comparative advantage, another approach to measuring knowledge competitiveness in a country is through the diffusion of knowledge across different design domains. Evidence shows that knowledge diffusion has a positive impact on economic growth (Perez-Trujillo and Lacalle-Calderon, 2020). According to Jun et al. (n.d.), knowledge diffusion reduces information asymmetry and promotes bilateral trade. Measuring knowledge diffusion within a country and across sectors can be accomplished through knowledge relatedness. Knowledge relatedness, measured by cross-domain patents, indicates the level of relatedness among patent classes (Kogler et al., 2013). The existing knowledge space within a region or country consisting of related knowledge can lead to future long-term competitive advantage.

Since the similar structure of design patent and patent data, design relatedness can also be captured using the similar method of technology relatedness. Knowledge relatedness is a necessity of technological diversification (Breschi et al., 2003), for firms, very low level or very high level of technological diversification is insufficient to encourage firm growth (Chen, Shih and Chang, 2012; J. Kim et al., 2016). This suggests that firms may need to specialise their technology in a sector. While from the perspective of economic growth, technological diversification is thought to promote national technological size and lead to increasing national productivity (Koren and Tenreyro, 2007). Moreover, empirical evidence shows that knowledge relatedness benefits economic transformation (Makri et al., 2009), therefore, the economy can quickly adapt to continuous global change. Therefore, design relatedness in a country is speculated to be positively related to corresponding exports.

H3: Design relatedness of exporting countries positively affects exports

3.2.2 Indirect Effect of Design on Exports

According to empirical evidence by Tintara (2020), product differentiation is a vital driver of firm comparative advantage. Furthermore, when firms export to foreign markets, product differentiation becomes much more important (Keskin et al., 2021). Product design plays a crucial role in determining both production costs and the attractiveness of the product to consumers in consumption markets (Desai et al., 2001). In fact, to some degree, product adaptation consists of firms' product differentiation strategies (Calantone, Tamer-Cavusgil et al., 2004).

On the other hand, there are natural differences between goods exported by foreign countries and local goods. However, international collaboration plays a significant role in marketing strategy decisions and new product development (Razavi-Hajiagha et al., 2022). With increased knowledge sharing among countries (Burke, 2011), existing international collaboration can determine the participation of firms in new markets and facilitate exports (Castellacci, 2014). Therefore, goods produced in different countries tend to be widely similar (Lall et al., 2006). Standardised goods and production technology can ultimately result in decreasing production differentiation worldwide.

Exporting countries may find themselves producing similar goods despite having sufficient design capabilities if their design knowledge is alike. In this context, measuring design similarity through the design-relatedness structure can serve as an indicator of design knowledge. However, design similarity may not directly affect exports but may impact the absolute effect in terms of industrial designs, including design capability and design relatedness.

H4: The positive effect of design capability on export value is reduced by design similarity between exporting and importing countries.

H5: The positive effect of design relatedness on export value is reduced by design similarity between exporting and importing countries.

When it comes to sectors with a high level of technological complexity, new product development typically requires more time than in other sectors. This is because the relevant knowledge involved in complex technology takes time for businesses to absorb (Rycroft, 2007). From a firm's perspective, technology complexity seems to moderate the effect of knowledge coupling on innovation performance (Yayavaram and Chen, 2015). When the technology complexity is low, knowledge coupling between businesses is likely to play a relatively effective role in innovation. These pieces of evidence focus on new knowledge absorption and new product development. However, technology complexity plays a different role once the comparative advantage of the technology has already been established.

Technology has a direct effect on the competitive advantage of businesses (Saeidi et al., 2019). In addition, it has been empirically evidenced that technology complexity has a positive effect on regional economic growth (Mewes and Broekel, 2022). For example, in the U.S. construction market, increasing technology complexity extends the existing competitive advantage, making it more attractive for foreign investors or practitioners (Tatum, 1988). Advanced technologies can act as a barrier for developing countries, which means that countries with technological advantages may consolidate their positions in the global market.

Balland, Boschma et al. (2019) proposed the technology complexity index, which utilises patent data to measure the complexity of a technology. In addition, design complexity is suggested as a measure for the knowledge complexity of different types of designs. Export similarity between countries can present obstacles in their relationships; nations with similar export structures are more likely to have international conflicts (Chatagnier and Kavaklı, 2017). Additionally, export similarity often results in bilateral trade friction, while lower levels of export similarity can boost and diversify bilateral trade through trade complementarity (P.-Z. Wang and Liu, 2015). Thus, design complexity seems to exacerbate the obstruction resulting from export similarity.

H6: The positive effect of design comparative advantage on export value is expected *to be more pronounced in sectors characterised by high design complexity.*

Revealed comparative advantage, unlike export similarity which indicates trade competition, measures competitiveness (Utkulu and Seymen, 2004). Design comparative advantage captures the exporting countries' advantages in terms of design and promotes exports. Increasing design complexity is likely to enhance this positive effect.

H7: The negative effect of export similarity between bilateral countries on trade value is enhanced by design complexity.

3.3 Data and Variables

To investigate the aforementioned hypothesis, a comprehensive dataset needs to be compiled using data collected from various sources. Given the complexity of the data utilised in this study, this section aims to delineate both the collected raw data and the constructed variables separately. The data subsection introduces the sources and coverage of the data for both countries and time. The variable construction subsection outlines the methodology employed to construct the variables.

3.3.1 Data

The dataset used in this study is derived from extensive data sources. To quantify industrial design, the design patent records accessed via Questel IP were utilised. The trade variable was generated using the export value acquired from UN Comtrade. Additionally, the regional trade agreement derived from Mario Larch's Regional Trade Agreements Database and the tariff rate data collected from TRAIN were employed as control variables.

The trade data is collected from UN Comtrade, which provides global goods and services trade data for detailed categories or commodities. The data employed in this study is the annual goods export value, collected at the 6-digit-commodity level (HS code). It encompasses 101 countries worldwide from 1989 to 2018. Therefore, the collected trade data consists of four levels: exporter country, importer country, commodity (classified by 6-digit HS code), and year. Due to the multidimensionality of this dataset, data visualisation cannot fully illustrate all perspectives. To demonstrate the temporal and spatial coverage of this data, Figure 3.1 presents the annual average aggregated export value of different countries worldwide during 2014.

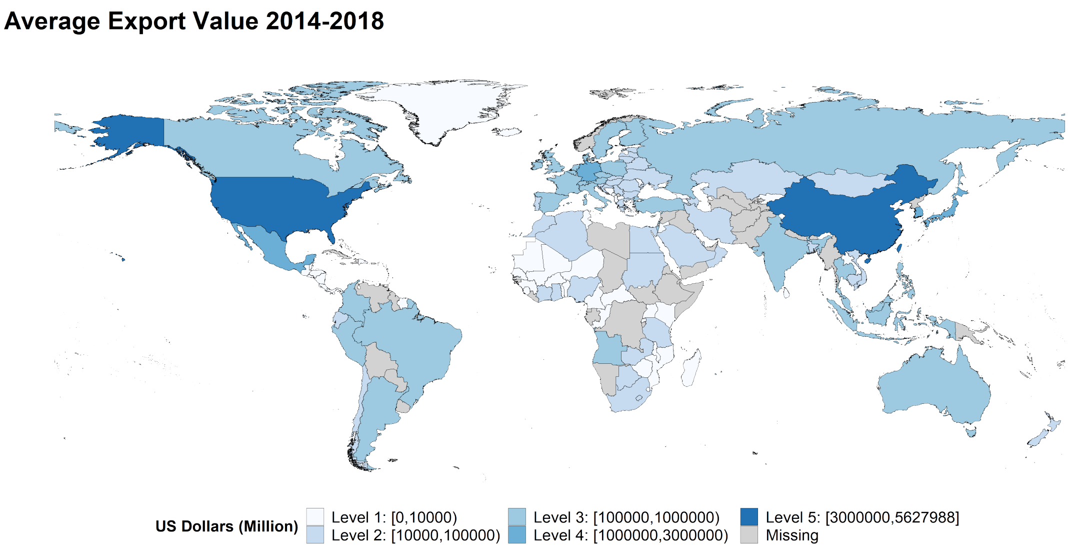


Figure 3.1: World Map - Annual Average Export During 2014-2018

Design data is collected from Questel IP, providing detailed information on each registered design record, including owners, application date, protected countries, and Locarno classes (the international classification specified for registering industrial designs). By categorising designs based on protection countries, application years, and Locarno classes using unique serial registration numbers, the count of registered designs can be calculated for each year, country, and Locarno class. Design data covers 181 countries and spans 30 years from 1989 to 2018. Additionally, this study calculates the cumulative number of registered designs over a 5-year duration. For instance, when calculating the cumulative count of registered designs in 2018, all designs registered during 2014-2018 are considered. Figure 3.2 presents the 5-year cumulative design count for 2018 using a geographic world map.

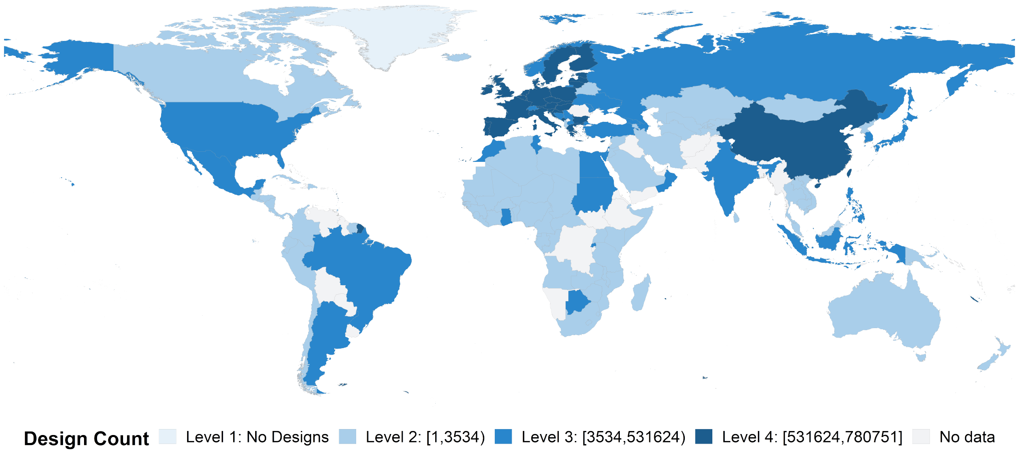


Figure 3.2: World Map - Cumulative Design Count During 2014-2018

Designs can be specified for various usages during registration, with applicants categorising designs according to the Locarno Classification, which consists of 33 categories as depicted in Figure 3.3. This figure highlights that the most frequently registered designs fall under Locarno-14, which covers information retrieval and recording equipment. The dark blue bars represent designs registered in earlier years, while the light blue bars represent more recent registrations. The evolutionary progress of industrial designs across different categories can be observed over the years. Figure 3.3 reveals that the category of logos and graphics (Locarno 32) represents a newly developed type of design, while registrations for other design types were widely achieved in the early years. Moreover, it is evident that the quantity of registered designs has increased over time.

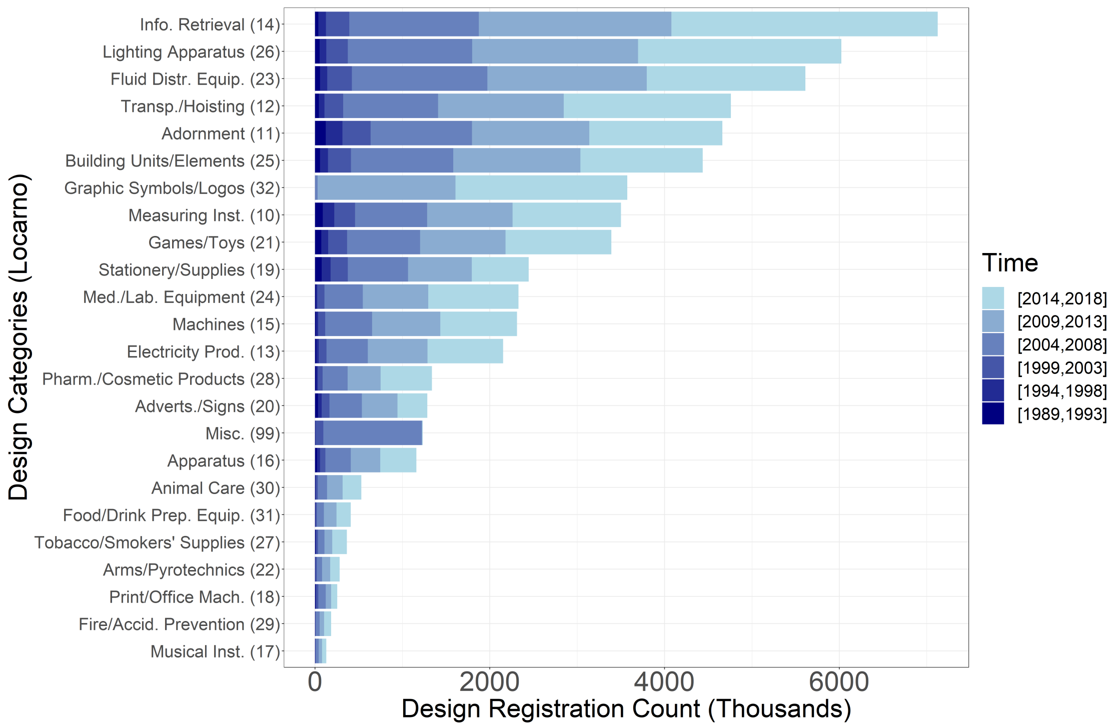


Figure 3.3: Bar Chart - Stack Design Count During 1989-2018

Trade data is used to generate the dependent variable, which is the export value. Design data is employed to construct different key explanatory variables based on the hypothesis to be tested. Additionally, other factors that may affect bilateral trade need to be controlled. Therefore, the regional trade agreement data collected from Mario Larch's database is employed as a control variable. Furthermore, the most favoured tariff rate collected from TRAIN is also utilised as another control variable. The time period of the tariff data and regional trade agreement data is restricted to 1989-2018 to align with the design and trade data. Figure 3.4 and Figure 3.5 present the trend of the most favoured nation tariff rate and the global intensity of signed regional trade agreements, respectively, from 1989 to 2018.

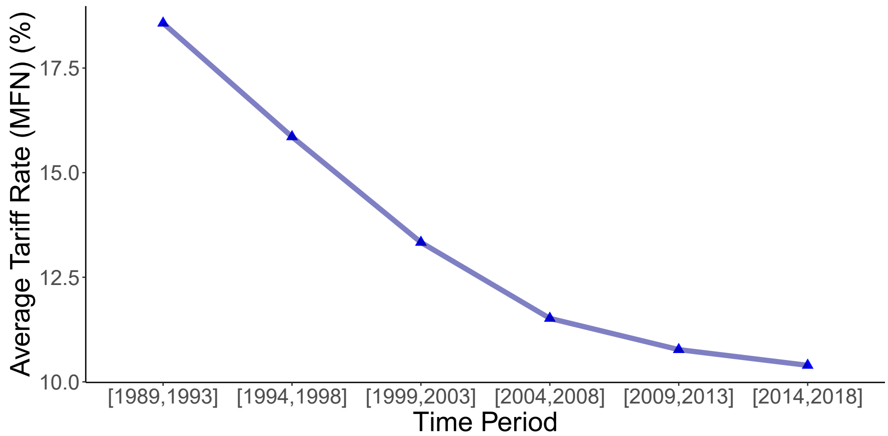


Figure 3.4: Line Chart: Average Tariff (Most Favored Nation) 1989-2018

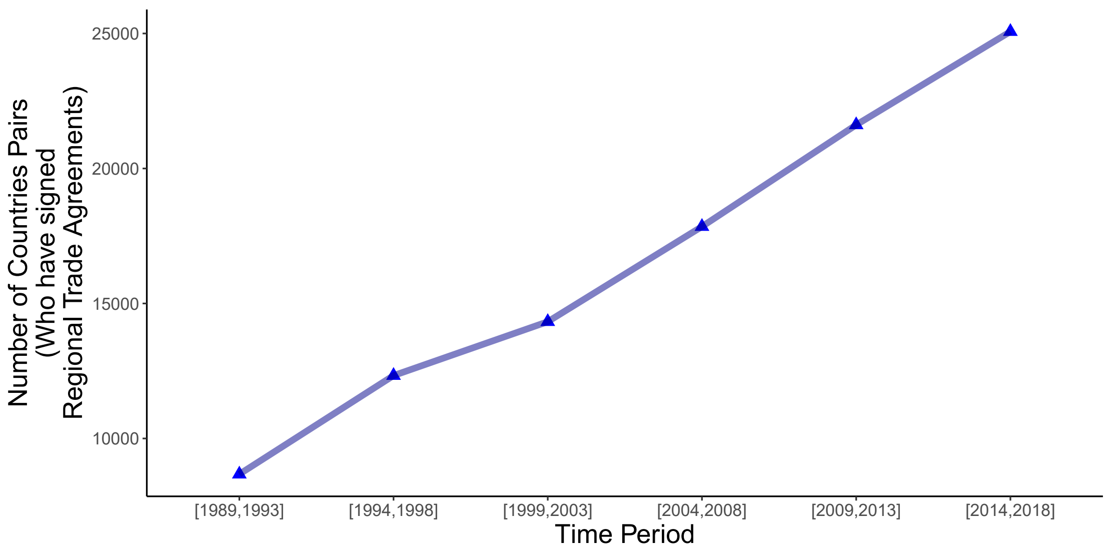


Figure 3.5: Line Chart: Number of Country Pairs (Signatories with Each Other) 1989-2018

3.3.2 Variable Construction

Using the aforementioned data, this section details the construction methodology for each variable. Firstly, the key explanatory variables, including design capability, design comparative advantage, total design relatedness, design relatedness density, design complexity, and design similarity, are introduced. Then, the control variables are presented, followed by the dependent variable, which is the export value.

3.3.2.1 Design Capability

Design capability is measured by the number of designs registered for protection in a specific country, denoted as country *i*. The variable $N_k^{t,i}$ represents the design capability of country *i* at time *t* for the commodity class *k*, which is categorised based on the 2-digit HS code (2017 version). The raw data covers a period of 30 years from 1989 to 2018, divided into six shorter periods: t_0 = 1989-1993, t_1 = 1994-1998, t_2 = 1999-2003, t_3 = 2004-2008, t_4 = 2009-2013, and t_5 = 2014-2018. All variables related to time identification are calculated based on these six periods, with observed values recorded over the corresponding time frames. Moreover, the variable is further transformed using the Inverse Hyperbolic Function (arsinh x) from the *base* package in R, and the values are transformed using the function *asinh()*. Figure 3.6 illustrates the distribution density of the calculated values of the design capability variable.

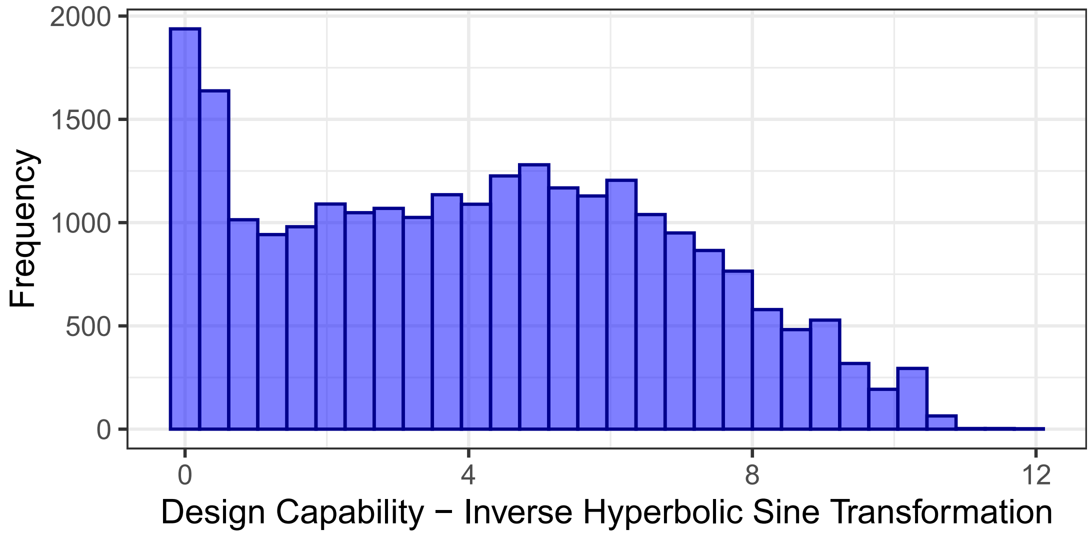


Figure 3.6: Distribution Density - Design Capability

3.3.2.2 Design Comparative Advantage

Building upon the variable construction of revealed comparative advantage (RCA) (Laursen, 2015) using international trade data, design comparative advantage (DCA) is constructed using design rights data. The measurement of RCA has been applied to innovation research using patent data to capture the revealed technological advantage (RTA) (Balland, Boschma et al., 2019). Given the similar structure of design rights data and patent data, the measurement method of RTA can also be applied to measure design comparative advantage. The definition expression of DCA is proposed in Equation (3.1).

$$DCA_k^{t,i} = \begin{cases} 1, \text{ if } \frac{N_k^{t,i} / \sum_k^{N_k^{t,i}}}{\sum_i N_k^{t,i} / \sum_i \sum_k N_k^{t,i}} > 1 \\ \\ 0, \text{ otherwise} \end{cases} \tag{3.1}$$

Here, $N_k^{t,i}$ denotes the count of registered designs under a specific 6-digit HS commodity *k* in a given period *t* within country *i*. The formula evaluates whether a country's count of designs in a particular commodity is greater than the commodity's global share during that time period *t*. Thus, $DCA_k^{t,i}$ captures whether a country *i* has a design comparative advantage in a time period *t* for a given commodity *k*. If DCA = 1, the country exhibits a design comparative advantage for a specific commodity *k*. Conversely, if DCA = 0, such an advantage is lacking. This variable does not require further rescaling. The summary statistics of computed values for this variable are shown in Table 3.1, with a mean value of 0.46 suggesting an even distribution of these dummy values.

Variable Name	Nbr. Obs	Nbr. Zeros	Min	Max	Mean	Std. Dev.
DCA (Country-product-year)	25054	13439	0	1	0.464	0.499

Table 3.1: Summary Statistics - Design Comparative Advantage

3.3.2.3 Total Design Relatedness

Kogler et al. (2013) employed a co-occurrence matrix to illustrate the *co-class* attribute of patent data. This matrix consists of rows and columns representing the same International Patent Classification (IPC) classes. Each cell in the matrix indicates the number of patents covering a combination of the corresponding two IPC classes, and the matrix is symmetrical.

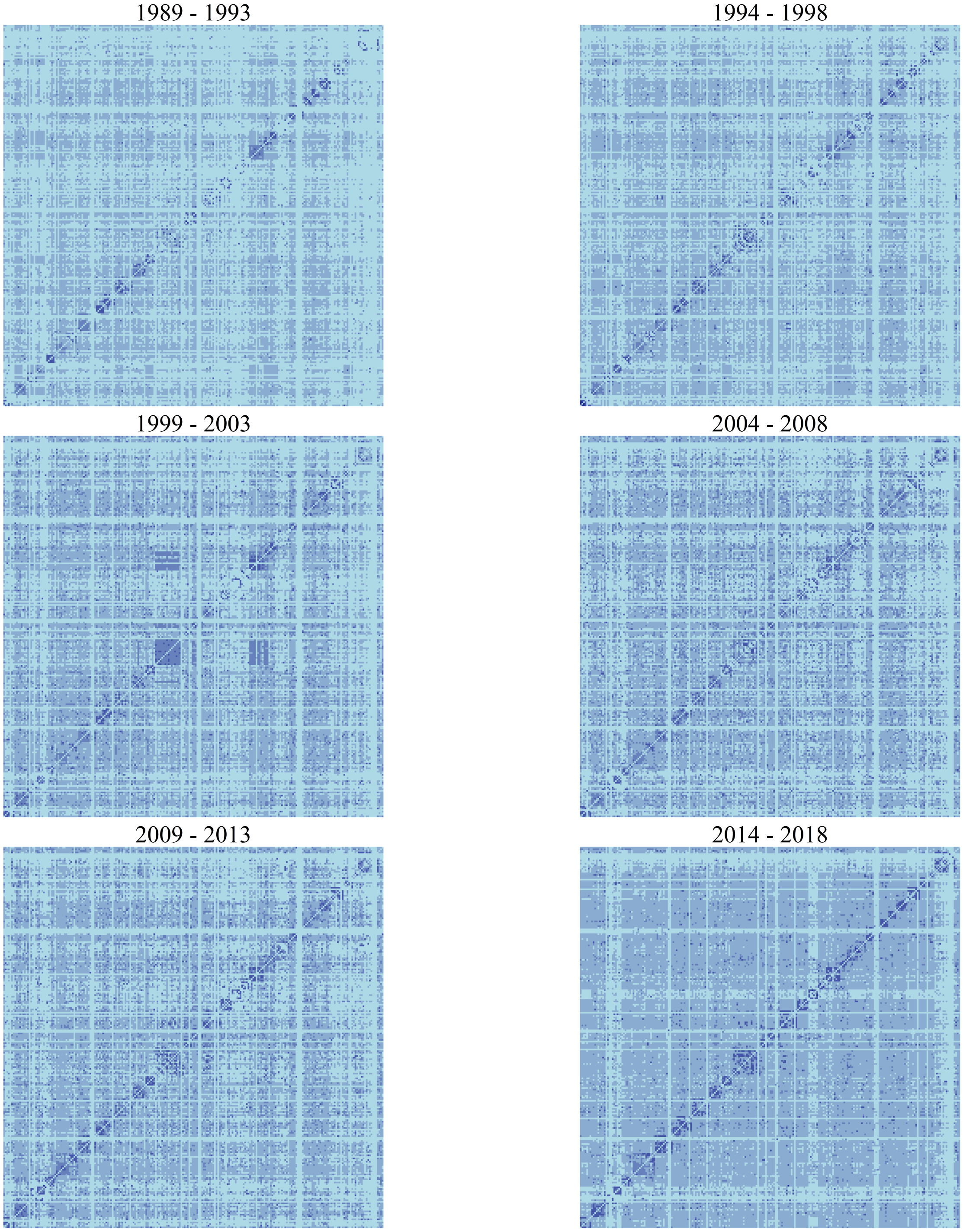


Figure 3.7: Heatmap - Design Relatedness

Like patents, design rights data also exhibit co-class propertiwhilees. Therefore, a similar methodology to that employed by Kogler et al. (2013) is adopted in this study. The rows and columns are labelled with Locarno class codes specific to designs. The resulting co-occurrence matrix consists of 238 rows and columns, each corresponding to a unique Locarno class, with the first class being 01-01 and the last class being 99-00. Importantly, the diagonal elements of the matrix are set to zero. To account for the thirty-year duration covered by the raw data (1989-2018) and separate the data, an individual co-occurrence matrix is generated for each country across six time periods, t_0 to t_5. Finally, the co-occurrence matrix is standardised using the probabilistic standardisation method developed by Steijn (2017), refined to enhance accuracy.

The resulting standardised matrix maintains a 238×238 structure consistent with the initial co-occurrence matrix. The standardised elements ($S^{t,i}_{L,L'}$) of this matrix correspond to measures of relatedness between distinct Locarno classes within a given year and country, while diagonal elements remain zero. The notion of relatedness pertains not only to similarities between design classes (Locarno), but also indicates the degree of knowledge diversification present within each class.

Aggregating the elements in the standardised matrices by columns results in the total design relatedness. This transformation aims to convert the disaggregated relatedness to the year-country-class level.

$$Total\ Design\ Relatedness_{L}^{t,i} = \sum_{L'} S_{L,L'}^{t,i}\ ^{1} \tag{3.2}$$

Total Design Relatedness measures the degree of similarity between Locarno class L (at a 4-digit level) and the remaining classes within country i during time period t. It provides an estimate of the design relatedness, signifying the extent of knowledge relatedness of a design class in a particular country and time period. The distribution density of computed values for the variable Total Design Relatedness is illustrated in Figure 3.8. This variable is computed for Locarno classes. Therefore, to compile variables into the same dataset, it needs to be further aligned with the HS commodity codes[2], and the variable will be written as $Total\ Design\ Relatedness_{k}^{t,i}$.

[1] Where L and L' denote the Locarno classes, t is the time period index, i indicates countries, and $S_{L,L'}^{t,i}$ represents elements in the standardised co-occurrence matrix

[2] See Appendix for the methods of correspndence between Locarno Classification and HS2017

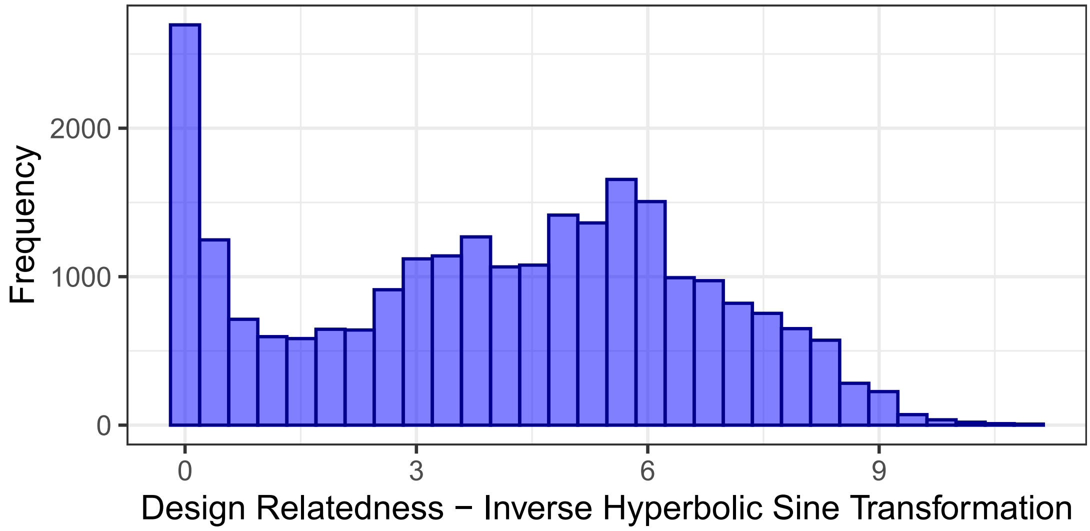


Figure 3.8: Distribution Density - Total Design Relatedness

3.3.2.4 Design Relatedness Density

The relatedness density in this study adopts the methodology of economic complexity theory proposed by Hidalgo, Klinger et al. (2007), but has been tailored specifically to analyse design rights data. By applying the variable construction outlined by Balland, Boschma et al. (2019), the design relatedness density has been modified to reflect a country or region level of dominance in a particular Locarno class (L) across the world in a given time interval (t). The probabilistic standardisation matrix is utilised to correct for any estimation errors, ensuring that *Relatedness Density* retains its probabilistic nature as an accurate measure of relatedness. The concept of design relatedness density describes the likelihood of connections around a design class. Unlike total relatedness, relatedness density is accompanied by the Design Comparative Advantage ($DCA_L^{t,i}$)

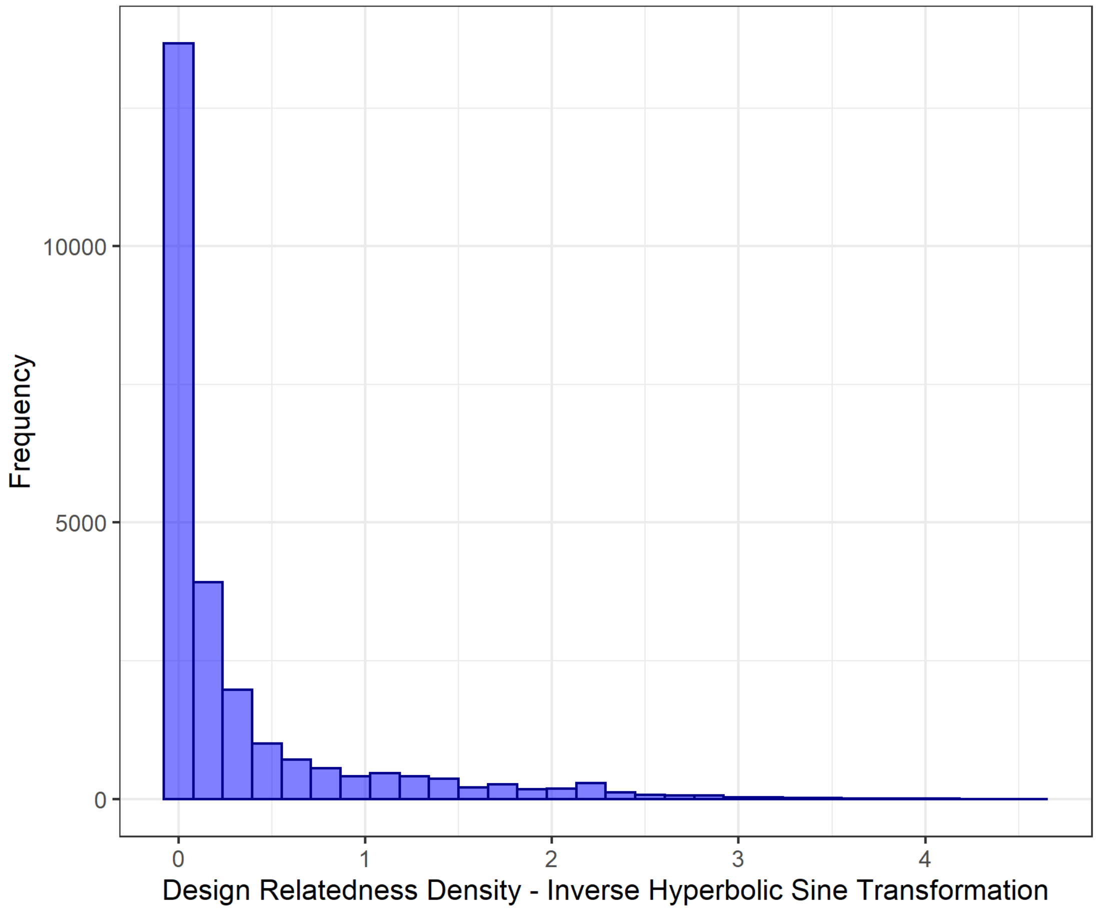
dummy variable. Here, design comparative advantage is measured according to Locarno classes using the calculation formula in Equation 3.3.

$$DCA_L^{t,i} = \begin{cases} 1, \text{ if } \frac{N_L^{t,i} / \sum_L^{N_L^{t,i}}}{\sum_i N_L^{t,i} / \sum_c \sum_L N_L^{t,i}} > 1 \\ 0, \text{ otherwise} \end{cases} \tag{3.3}$$

Here, $N_L^{t,c}$ denotes the count of registered designs under a specific Locarno class L in a given year t within country c. The formula evaluates whether a country or region's count of designs in a particular Locarno class is greater than the classification's global share during that year t. Thus, $DCA_L^{t,i}$ captures whether a country i has a design comparative advantage in a time period t for a given design class L. If DCA = 1, then the country exhibits a design comparative advantage for a specific Locarno class L. Conversely, if DCA = 0, such an advantage is lacking. However, it should be noted that the inclusion of DCA in the relatedness density measure omits any relatedness originating from Locarno classes not conducive to design advantage within country i during time period t. The formula can be written as Equation 3.4.

$$Relatedness\ Density_L^{t,i} = \frac{Total\ Relatedness_L^{t,i} \times DCA_L^{t,i}}{\sum_i Total\ Relatedness_L^{t,i}} \times 100\% \tag{3.4}$$

When using this variable in estimation, Locarno classification needs to be transformed into HS sectors. Thus, the variable can be written as $Relatedness\ Density_k^{t,i}$ (where k denotes HS sectors). Given the aforementioned benefits of the design relatedness density measure, it is considered a potential substitute for total design relatedness when conducting robustness tests. The distribution density of computed values for the relatedness density variable is shown in Figure 3.9.



.

Figure 3.9: Histogram - Distribution Density of Design Relatedness Density

3.3.2.5 Design Complexity

By aligning the design data with international trade data, Locarno classification of designs can be converted to the Harmonised System (HS) classification (version 2017). The number of designs registered in a country i at time t is expressed as $N_k^{t,i}$, where k indicates products measured based on HS2017. Additionally, design comparative advantage can be measured by HS sectors, written as $DCA_k^{t,i}$.

$DCA_k^{t,i}$ has a panel data structure, which can be transformed into matrices M with elements $M_{i,k}^t$. Each matrix M corresponds to a specific time interval t and contains rows representing countries and columns representing products.

Following existing research (Balland, Boschma et al., 2019; Hidalgo and Hausmann, 2009), $B = M^T M$ can be generated. The matrix B needs to be row-standardised to obtain the stochastic matrix, with the diagonal elements set to zero. Then, the second eigenvector $\vec{v}$ of the stochastic matrix is taken, and the design complexity can be calculated using the standardised $\vec{v}$: $Design\ Complexity_{k,t} = \frac{\vec{v} - <\vec{v}>}{sd(\vec{v})}$. In other words, the z-score of the second eigenvector of the resulting stochastic matrix is taken as the design complexity index.

3.3.2.6 Export Similarity

Bahar et al. (2014) employed Pearson Correlation to measure the similarity of the export structure between bilateral countries. Following the calculation of design comparative advantage, $R_p^{t,ik} = \text{arsinh}(\frac{X_p^{t,ik}/\sum_p X_p^{t,ik}}{\sum_c X_p^{t,ik}/\sum_c \sum_p X_p^{t,ik}})$. Here, X represents the export value, i denotes the exporting country, t is the time interval, k indicates the HS sector at the 2-digit level, and p denotes HS products at the 6-digit level that belong to the 2-digit sector k. Export similarity can be written as Equation (3.5):

$$Export\ Similarity_k^{t,ij} = \frac{\sum_p [(R_p^{t,ik} - \overline{R_p^{t,ik}})(R_p^{t,jk} - \overline{R_p^{t,jk}})]}{\sqrt{\sum_p (R_p^{t,ik} - \overline{R_p^{t,ik}})^2 \times \sum_p (R_p^{t,jk} - \overline{R_p^{t,jk}})^2}} \tag{3.5}$$

It measures the extent to which a country exports similar products compared to another country within a product group k. It can be considered as the similarity of the export structure of a group of products.

3.3.2.7 Design Similarity

Similar to export similarity, in design similarity, $R_p^{t,c,k}$ is defined as $arsinh(\frac{Total\ Relatedness_L^{t,ik}/\sum_L Total\ Relatedness_L^{t,ik}}{\sum_i Total\ Relatedness_L^{t,ik}/\sum_i \sum_L Total\ Relatedness_L^{t,ik}})$. The subscript p is replaced by L, which represents the Locarno class at the 2-digit level. Design similarity captures the structural proximity of the design relatedness between two different countries within each 2-digit HS group.

$$Design\ Similarity_k^{t,ij} = \frac{\sum_L[(R_L^{t,ik} - \overline{R_L^{t,ik}})(R_L^{t,jk} - \overline{R_L^{t,jk}})]}{\sqrt{\sum_L(R_L^{t,ik} - \overline{R_L^{t,jk}})^2 \times \sum_L(R_L^{t,jk} - \overline{R_L^{t,jk}})^2}} \tag{3.6}$$

Design similarity and export similarity both range from -1 to 1. However, since the principle of the similarity measure is Pearson Correlation, values of exactly -1 or 1 are statistically impossible. Observations with design or export similarity values of 1 or -1 are considered estimation errors and omitted, as it would be unreasonable for two countries to have exactly the same design or export structures.

3.3.2.8 Other Controls

Export similarity is not a key explanatory variable in this study; therefore, it is regarded as one of the control variables. However, when examining the interactive effect of design complexity and export similarity, the interaction term involving export similarity will be the focus. Regional Trade Agreement is another control variable that captures the relations between bilateral countries from a policy perspective. Regional Trade Agreement is a dummy variable in the model, measuring whether two parties have signed a regional trade agreement during the corresponding time period. It is at the country-country-year level, ignoring the commodities. Other control variables aim to account for factors of importing countries. Tariff is measured at the level of the importing country, year, and commodity, representing the average Most Favoured Nation tariff per 2-digit

HS group across all 6-digit products for each importing country j, time period t, and 2-digit commodity k.

3.3.3 Summary of Variables and Corresponding Data Sources

The raw data sources corresponding to the variables employed in this study are summarised in Table 3.2.

Variable Name	Raw Data Source
Design Capability	Questel IP
Design Comparative Advantage	Questel IP
Design Relatedness	Questel IP
Design Similarity	Questel IP
Export Value	UN Comtrade
Export Similarity	UN Comtrade
Tariff	TRAIN
Regional Trade Agreement	Mario Larch's Regional Trade Agreements Database

Table 3.2: Summary of Data Sources of Chapter 3

3.4 Methodology

In the methodology section, the estimation strategy of hypotheses will be introduced. This is divided into two parts: (i) The baseline estimation includes the estimation of the direct effect of design capability and design relatedness of exporting countries on trade value. (ii) The interactive effect estimation introduces the indirect effect of design similarity and design complexity on trade value.

In the context of explaining export values with other variables, the gravity model is widely employed in research. Pfaffermayr (2023) discusses its use in cross-sectional analysis, while Capoani (2023) also recognises its prevalence in trade analysis. Additionally, Silva and Tenreyro (2006) highlights the bias introduced by Jensen's inequality in the gravity model, addressed by employing PPML (Poisson Pseudo Maximum Likelihood) estimation as a solution (Mnasri and Nechi, 2021).

In gravity models, fixed effects are commonly utilised to estimate exporter- and importer-invariant variables, enhancing the understanding of trade flow determinants. Therefore, fixed effects are incorporated into the estimation process. However, the presence of collinearity may lead to the omission of certain explanatory variables in gravity models, a topic to be addressed in subsequent subsections for different model specifications.

3.4.1 Baseline Estimation

To have an initial look at the direct effect of design capability and design relatedess on trade value, the model specification is proposed in Equation (3.7).

$$
\begin{aligned}
Export\ Value_{ijk,t} =& \beta_0 + \beta_1 Design\ Capability_{ik,t-1} \\
& + \beta_2 DesignComparativeAdvantage_{ik,t-1} \\
& + \beta_3 DesignRelatedness_{jk,t-1} \\
& + \beta_4 ExportSimilarity_{ijk,t-1} \\
& + \beta_5 DesignCapability_{jk,t-1} \\
& + \beta_6 DesignRelatedness_{jk,t-1} \\
& + \beta_7 Tariff_{jk,t-1} + \beta_8 RTA_{ij,t-1} \\
& + \gamma_{ij} + \delta_t + \zeta_k + \epsilon_{ijkt}
\end{aligned} \tag{3.7}
$$

Where *i* and *j* denote the exporting country and the importing country respectively, *k* indicates goods sectors which are classified by HS2017, and *t* denotes the time dimension.

Design Capability is the number of design registrations in a country, *Design Relatedness* indicates the degree of relatedness between different types of designs within a country, *Export Similarity* is the similarity of export structure between both parties of bilateral trade, *Tariff* indicates the MFN tariff of import countries, and *RTA* is a dummy variable indicating the presence of regional trade agreements between bilateral countries.

For *Design Capability*, *Design Relatedness*, and *Design Comparative Advantage*, these variables can be constructed at the unilateral-country level for both exporting and importing countries. These variables, when constructed for the exporting countries, serve as key explanatory variables in this study. If the variables are measured for importing countries, they would be considered as control variables in the model.

γ_{ij} is the fixed effect that captures unobserved time-invariant relations between bilateral countries, e.g. the geographic distance, colonial history, and common language, etc. The fixed effect δ_t can capture the global changes which do not specifically pertain to any single country. The sectoral fixed effect ζ_k can capture unobservable sectoral heterogeneity relevant to both trade and design factors. ϵ_{ijkt} is the error term.

The estimation is conducted by PPML (Poisson Pseudo-Maximum Likelihood). This requires a log transformation for non-dummy independent variables. However, since key explanatory variables of this research involve a large number of zeros, the log transformation will be replaced by the inverse hyperbolic sine ($\ln(x + \sqrt{x^2+1})$) or inverse hyperbolic tangent ($\frac{1}{2}\ln(\frac{1+x}{1-x})$) transformation methods[3]. Variables of design capability and design relatedness are transformed with the inverse hyperbolic sine, while the variables of design similarity and export similarity are transformed with the inverse hyperbolic tangent. The transformation method is determined by numeric features of the data as presented in the data description section.

[3]The function *arsinh()* in the *base* package of R is employed for the inverse hyperbolic sine transformation. The function *artanh()* in the *base* package of R is employed for the inverse hyperbolic tangent transformation.

In this model specification, it can be suspected that simultaneity between design variables and export value may occure. Which may result in endogeneity. To remove the endogeneity caused by time, the estimation takes the one-order lag, thus the time identifier for independent variables is written as the *minus 1* (*t-1*).

Via baseline estimation, Hypothesis 1, Hypothesis 2, and Hypothesis 3 can be tested directly. Variables *Design Capability*, *Design Comparative Advantage*, and *Design Relatedness* are expected to generate significant and positive estimated coefficients, corresponding to the hypotheses tested in the baseline estimation.

3.4.2 Interactive Effect

Interactive estimation aims to test the indirect effect of design variables based on the previous baseline estimation. It also continues the model specification with the same fundamental variables. Likewise, the interactive effect is estimated by PPML.

3.4.2.1 Indirect Effect of Design Similarity on Exports through Design Capability

To examine the extent to which design similarity affects export value by influencing design capability, the interaction term *Design Capability*$_{ik,t-1}$ $\times$ *Design Similarity*$_{ijk,t-1}$ is added to the benchmark model specification. See Equation (3.8) for the estimation model. In order to control for the absolute effect of variables design capability and design similarity on export value, the single variables without interaction are also included.

$$\begin{aligned}
Export\ Value_{ijk,t} =& \beta_0 + \beta_1 Design\ Capability_{ik,t-1} \\
& + \beta_2 Design\ Similarity_{ik,t-1} \\
& + \beta_3 Design\ Capability_{ik,t-1} \\
& \quad \times Design\ Similarity_{ik,t-1} \\
& + \beta_4 Design\ Comparative\ Advantage_{ik,t-1} \\
& + \beta_5 Design\ Relatedness_{jk,t-1} \\
& + \beta_6 Export\ Similarity_{ijk,t-1} \\
& + \beta_7 Design\ Capability_{jk,t-1} \\
& + \beta_8 Design\ Relatedness_{jk,t-1} \\
& + \beta_9 Tariff_{jk,t-1} + \beta_{10} RTA_{ij,t-1} \\
& + \gamma_{ij} + \delta_t + \zeta_k + \epsilon_{ijkt}
\end{aligned} \tag{3.8}$$

In this estimation, the focus is on the interactive effect between design capability and design similarity, as well as the absolute effect of design capability of exporting countries (primary examination of Hypothesis 4 is done via this model). Design capability is expected to have a significant and positive absolute effect on exports, which means the estimated coefficient of the variable *Design Capability*$_{ik,t-1}$ is expected to be significant and positive. Additionally, the coefficient of the interaction term *Design*

Capability$_{ik,t-1}$ $\times$ *Design Similarity*$_{ijk,t-1}$ is expected to be negative and significant. This suggests that a relatively high design similarity between bilateral countries weakens the positive effect of design capability.

3.4.2.2 Indirect Effect of Design Similarity on Exports through Design Relatedness

By examining the interactive effect of design similarity and design relatedness, Hypothesis 5 can be tested. Based on the benchmark estimation, *Design Relatedness*$_{ik,t-1}$ $\times$ *Design Similarity*$_{ik,t-1}$ is added to the model. Meanwhile, the single variables *Design Relatedness*$_{ik,t-1}$ and *Design Similarity*$_{ik,t-1}$ are added to control the absolute effect. The estimation model is written as Equation (3.9).

$$
\begin{aligned}
Export\ Value_{ijk,t} = &\beta_0 + \beta_1 Design\ Capability_{ik,t-1} \\
&+ \beta_2 DesignComparativeAdvantage_{ik,t-1} \\
&+ \beta_3 DesignRelatedness_{jk,t-1} \\
&+ \beta_4 DesignSimilarity_{jk,t-1} \\
&+ \beta_5 (Design\ Relatedness_{ik,t-1} \\
&\quad \times Design\ Similarity_{ik,t-1}) \\
&+ \beta_6 ExportSimilarity_{ijk,t-1} \\
&+ \beta_7 DesignCapability_{jk,t-1} \\
&+ \beta_8 RelatednessDensity_{jk,t-1} \\
&+ \beta_9 Tariff_{jk,t-1} + \beta_{10} RTA_{ij,t-1} \\
&+ \gamma_{ij} + \delta_t + \zeta_k + \epsilon_{ijkt}
\end{aligned} \tag{3.9}
$$

The absolute effect of design relatedness in exporting countries is expected to be positive and significant, which means the estimated coefficient of design relatedness of exporting countries is expected to be positive and significant. Meanwhile, the interactive effect of design relatedness and design similarity is expected to be negative and significant. This suggests that design similarity weakens the positive effect of design relatedness in exporting countries on export value. Therefore, the estimated coefficient of *Design Relatedness*$_{ik,t-1}$ $\times$ *Design Similarity*$_{ik,t-1}$ is expected to be negative and significant.

3.4.2.3 Indirect Effect of Design Complexity on Exports through Design Comparative Advantage

As it is written in Equation (3.10), the interactive effect of design complexity and design comparative advantage in exporting countries is estimated by the interaction term $\textit{Design Comparative Advantage}_{ik,t-1} \times \textit{Design Complexity}_{k,t-1}$. The absolute effect of variables design comparative advantage and design complexity is also controlled.

$$
\begin{aligned}
Export\ Value_{ijk,t} = & \beta_0 + \beta_1 Design\ Capacity_{ik,t-1} \\
& + \beta_2 DesignComparativeAdvantage_{ik,t-1} \\
& + \beta_3 DesignComplexity_{ik,t-1} \\
& + \beta_4 DesignComparativeAdvantage_{ik,t-1} \\
& \quad \times Design\ Complexity_{k,t-1} \\
& + \beta_5 RelatednessDensity_{jk,t-1} \\
& + \beta_6 ExportSimilarity_{ijk,t-1} \\
& + \beta_7 DesignCapacity_{jk,t-1} \\
& + \beta_8 RelatednessDensity_{jk,t-1} \\
& + \beta_9 Tariff_{jk,t-1} + \beta_{10} RTA_{ij,t-1} \\
& + \gamma_{ij} + \delta_t + \zeta_k + \epsilon_{ijkt}
\end{aligned}
\tag{3.10}
$$

Hypothesis 6 is tested by examining the estimated coefficients of variables *Design Comparative Advantage*$_{ik,t-1}$ and *Design Comparative Advantage*$_{ik,t-1}$ $\times$ *Design Complexity*$_{k,t-1}$. The coefficient of *Design Comparative Advantage*$_{ik,t-1}$ is expected to be positive and significant, suggesting that design comparative advantage in exporting countries has a positive absolute effect on export value. The coefficient of the interaction term is also expected to be significant and positive, indicating that the effect of design comparative advantage in exporting countries is larger in sectors with higher design complexity.

3.4.2.4 Design Complexity on Export Similarity

The interactive effect of design complexity and export similarity is examined by adding the interaction term *Export Similarity*$_{ijk,t-1}$ $\times$ *Design Complexity*$_{k,t-1}$ to the benchmark model specification. The variables *Export Similarity*$_{ijk,t-1}$ and *Design Complexity*$_{k,t-1}$ are controlled to capture the corresponding direct effect. See Equation (3.11) for the estimation model.

$$\begin{aligned} Export\ Value_{ijk,t} = & \beta_0 + \beta_1 Design\ Capability_{ik,t-1} \\ & + \beta_2 Design\ Comparative\ Advantage_{ik,t-1} \\ & + \beta_3 Design\ Relatedness_{jk,t-1} \\ & + \beta_4 Export\ Similarity_{ijk,t-1} \\ & + \beta_5 Design\ Complexity_{k,t-1} \\ & + \beta_6 Export\ Similarity_{ijk,t-1} \\ & \quad \times Design\ Complexity_{k,t-1}) \\ & + \beta_7 Design\ Capability_{jk,t-1} \\ & + \beta_8 Design\ Relatedness_{jk,t-1} \\ & + \beta_9 Tariff_{jk,t-1} + \beta_{10} RTA_{ij,t-1} \\ & + \gamma_{ij} + \delta_t + \zeta_k + \epsilon_{ijkt} \end{aligned} \tag{3.11}$$

This estimation focuses on the coefficients of both *Export Similarity*$_{ijk,t-1}$ $\times$ *Design Complexity*$_{k,t-1}$ and *Export Similarity*$_{ijk,t-1}$. The expected inhibiting effect of export similarity between bilateral countries on exports is corresponding to the significantly estimated negative sign of the coefficient of *Export Similarity*$_{ijk,t-1}$. The coefficient of *Export Similarity*$_{ijk,t-1}$ $\times$ *Design Complexity*$_{k,t-1}$ is expected to be statistically negative and significant, which implies that the inhibiting effect of export similarity tends to be larger in sectors with a higher level of design complexity.

3.5 Results

3.5.1 Baseline Estimation

As shown in Table (3.3), the design capability of exporting countries plays a positive role in promoting exports. Upon the addition of new variables, such as the design comparative advantage and design relatedness, the estimated coefficient for the variable design capability of exporting countries remains positive and statistically significant. These findings are consistent with our expectations and provide empirical evidence for the promotion effect of the design capability of exporting countries on exports.

Furthermore, Column (2) in Table (3.3) shows that the design comparative advantage of exporting countries positively affects exports. When the new variable of design relatedness of exporting countries was added to the model, as seen in Column (3), the corresponding estimated coefficient was even larger than before. In addition, capturing the design relatedness of exporting countries improved the significance level of the estimated coefficients of design comparative advantage for exporting countries.

The positive impact of design relatedness in exporting countries on exports is evident from the estimated coefficients presented in Column (3) of Table (3.3). The variable, Design Relatedness$_{ik,t-1}$, has a statistically significant and positive coefficient value. Since this variable is included only in one regression model, the robustness of the results cannot be discussed in benchmark estimation.

The export similarity between two countries has a statistically significant and negative effect on trade value. The most favoured nation tariff of importing countries also has a negative effect on trade value. However, regional trade agreements do not seem to have any impact on trade value. It is important to note that the estimation is based on sectoral panel data, and the variable of regional trade agreements does not involve the sectoral level, which may result in estimation bias.

Design capability and comparative advantage of importing countries positively affect trade value. This is because innovation capability and advantage represent the level of economic development, and developed countries tend to trade more. However, the design-relatedness of importing countries negatively affects trade value, suggesting that knowledge related to design in a country is a competitive advantage. Considering the positive role of design-relatedness in exporting countries, it can bring about a trade surplus for economies.

Dep.Variable	(1) Exports	(2) Exports	(3) Exports
Design Capability$_{ik,t-1}$	0.1264***	0.1214***	0.1011***
	(0.0216)	(0.0206)	(0.0191)
Design Comparative Advantage$_{ik,t-1}$		0.1004*	0.1084**
		(0.0396)	(0.0395)
Design Relatedness$_{ik,t-1}$			0.0551***
			(0.0114)
Export Similarity$_{ijk,t-1}$	-0.7407***	-0.7493***	-0.7392***
	(0.1024)	(0.1018)	(0.1015)
Design Capability$_{jk,t-1}$	0.0303*	0.0300*	0.0300*
	(0.0146)	(0.0147)	(0.0146)
Design Relatedness$_{jk,t-1}$	-0.0302**	-0.0305**	-0.0238*
	(0.0116)	(0.0116)	(0.0117)
Design Comparative Advantage$_{jk,t-1}$	0.0763*	0.0734*	0.0737*
	(0.0356)	(0.0356)	(0.0359)
Tariff$_{jk,t-1}$	-0.9223**	-0.9188**	-0.9213**
	(0.3461)	(0.3458)	(0.3467)
rta	0.0544	0.0552	0.0787
	(0.0688)	(0.0683)	(0.0697)
Constant	18.9888***	18.9832***	18.7243***
	(0.1868)	(0.1824)	(0.1940)
Fixed Effect	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk
Pseudo R^2	0.8441	0.8443	0.8446
Log-likelihood	-5.7430e+12	-5.7352e+12	-5.7245e+12
Nbr.Obs	795410	795410	795410

Table 3.3: Baseline Estimation - Direct Effect of Industrial Design on Exports

3.5.2 Interavtive Effect

In all models presented in Table (3.4), the variables of *Design Capability*$_{ik,t-1}$, *Design Comparative Advantage*$_{ik,t-1}$, and *Design Relatedness*$_{ik,t-1}$ retain a positive and significant effect on export value. This provides robustness to Hypothesis 1, Hypothesis 2, and Hypothesis 3. Moreover, it establishes a benchmark for further interactive effect estimations. As design capability, design comparative advantage, and design relatedness of exporting countries show a positive absolute effect on export value, their interactive effects with other variables can be analysed based on this baseline.

In addition, the estimation of export similarity is not the main focus of this study. However, it serves as a baseline to test the indirect effect of design complexity. It can be observed that the export similarity has a statistically significant and negative impact on trade, implying that two countries with similar export structures are less likely to engage in trade.

According to the estimated coefficients of interaction terms of *Design Capability*$_{ik,t-1}$ $\times$ *Design Similarity*$_{ijk,t-1}$ and Design Relatedness$_{ik,t-1}$ $\times$ *Design Similarity*$_{ijk,t-1}$ (Table (3.4)), the negative and significant estimates suggest that design similarity has a negative effect on the design capability and design relatedness of exporting countries. This implies that design similarity has a moderating effect on trade value, and the design capability and design relatedness of exporting countries are the mediums through which this effect works.

The negative estimated coefficient for *Design Complexity*$_{k,t-1}$ $\times$ *Export Similarity*$_{ijk,t-1}$ (Model (3) in Table (3.4)) suggests that export similarity is a larger barrier in product sectors with a higher level of design complexity. Meanwhile, the positive estimated coefficient for *Design Complexity*$_{k,t-1}$ $\times$ *Design Comparative Advantage*$_{ijk,t-1}$ implies that the existing design comparative advantage can be strengthened in product sectors with a high level of design complexity.

Besides, the variables of design similarity and design complexity do not directly affect trade. The estimated coefficients of these two single variables (*Design Complexity*$_{k,t-1}$ and *Design Similarity*$_{ijk,t-1}$) are not statistically significant. It can be concluded that design similarity and design complexity play a moderating role in trade instead of having a direct effect.

In regards to other control variables, only the most favoured nation tariff has retained its significance and negative impact on trade. However, design capability, design relatedness, and design comparative advantage have lost their previous significance in the baseline estimation. As a result, the role of design variables in importing countries cannot be confirmed statistically. Additionally, the variable of regional trade agreement is statistically insignificant.

	(1)	(2)	(3)	(4)
Dependent Variable	Exports	Exports	Exports	Exports
Design Capability$_{ik,t-1}$	0.1022***	0.0969***	0.0995***	0.1025***
	(0.0191)	(0.0192)	(0.0190)	(0.0193)
Design Comparative Advantage$_{ik,t-1}$	0.1126**	0.1096**	0.1085**	0.0936*
	(0.0395)	(0.0394)	(0.0397)	(0.0399)
Design Relatedness$_{ik,t-1}$	0.0553***	0.0587***	0.0557***	0.0557***
	(0.0115)	(0.0114)	(0.0113)	(0.0114)
Design Capability$_{ik,t-1}$ $\times$ Design Similarity$_{ijk,t-1}$	-0.0305**			
	(0.0114)			
Design Relatedness$_{ik,t-1}$ $\times$ Design Similarity$_{ijk,t-1}$		-0.0336*		
		(0.0137)		
Design Complexity$_{k,t-1}$ $\times$ Export Similarity$_{ijk,t-1}$			-0.2181**	
			(0.0775)	
Design Complexity$_{k,t-1}$ $\times$ Design Comparative Advantage$_{ijk,t-1}$				0.0915*
				(0.0373)
Design Similarity$_{ijk,t-1}$	0.1349	0.1307		
	(0.0848)	(0.0917)		
Design Complexity$_{k,t-1}$			-0.0222	-0.0658*
			(0.0218)	(0.0275)
Export Similarity$_{ijk,t-1}$	-0.7300***	-0.7296***	-0.7199***	-0.7365***
	(0.1013)	(0.1013)	(0.0992)	(0.1013)
Design Capability$_{jk,t-1}$	0.0316*	0.0314*	0.0284	0.0304*
	(0.0145)	(0.0145)	(0.0146)	(0.0146)
Design Relatedness$_{jk,t-1}$	-0.0238*	-0.0234*	-0.0227	-0.0238*
	(0.0117)	(0.0117)	(0.0116)	(0.0116)
Design Comparative Advantage$_{jk,t-1}$	0.0729*	0.0726*	0.0707*	0.0691
	(0.0360)	(0.0360)	(0.0357)	(0.0357)
Tariff$_{jk,t-1}$	-0.9171**	-0.9199**	-0.9279**	-0.9215**
	(0.3469)	(0.3470)	(0.3472)	(0.3463)
Regional Trade Agreement$_{ij,t-1}$	0.0918	0.0936	0.0801	0.0879
	(0.0699)	(0.0700)	(0.0698)	(0.0702)
Constant	18.6950***	18.7127***	18.7401***	18.7162***
	(0.1955)	(0.1951)	(0.1951)	(0.1978)
Fixed Effect	ij k t	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk	ijk
Pseudo R^2	0.8447	0.8447	0.8447	0.8447
Log-likelihood	-5.7201e+12	-5.7202e+12	-5.7193e+12	-5.7207e+12
Nbr.Obs	795410	795410	795410	795410

Table 3.4: Interactive Effect

3.6 Robustness Test

3.6.1 Model Specification of Baseline Estimation

Replacing the set of fixed effects in baseline estimation by fixed effects γ_{ij} and η_{jkt} can capture more unobserved factors in importing countries at sector-year level. As a result, the estimation can reduce systemic errors[4] more than the original baseline. See Equation (3.12) for Model Specification. This set of fixed effects is used only for robustness testing as it omits all controls at the importer-sector-year level.

$$\begin{aligned} Trade\ Value_{ijk,t} =& \beta_0 + \beta_1 \times Design\ Capacity_{ik,t-1} \\ & + \beta_2 \times Design\ Comparative\ Advantage_{ik,t-1} \\ & + \beta_3 \times Export\ Similarity_{ijk,t-1} \\ & + \beta_4 \times RTA_{ij,t-1} \\ & + \gamma_{ij} + \eta_{jkt} + \epsilon_{ijkt} \end{aligned} \tag{3.12}$$

As shown in Table (3.5), after adding strengthened fixed effects, all design variables of exporting countries maintain their significant and positive results. This suggests that Hypothesis 1, Hypothesis 2, and Hypothesis 3 pass the robustness test. In other words,

[4]The systemic errors here refer to the consistent biases or inaccuracies of estimation, which are predictable and affecting results.

design capability, design comparative advantage, and design relatedness of exporting countries can be considered to positively impact the export value.

	(1)	(2)	(3)
Dependent Variable	Exports	Exports	Exports
Design Capability$_{ik,t-1}$	0.1189***	0.1148***	0.0849***
	(0.0216)	(0.0206)	(0.0186)
Design Comparative Advantage$_{ik,t-1}$		0.0800*	0.0885*
		(0.0378)	(0.0373)
Design Relatedness$_{ik,t-1}$			0.0781***
			(0.0098)
Export Similarity$_{ijk,t-1}$	-0.9863***	-0.9951***	-0.9781***
	(0.1160)	(0.1155)	(0.1148)
Regional Trade Agreement$_{ij,t-1}$	0.0313	0.0275	0.0571
	(0.0518)	(0.0518)	(0.0581)
Constant	19.2462***	19.2398***	18.9378***
	(0.1756)	(0.1695)	(0.1673)
Fixed Effect	ij jkt	ij jkt	ij jkt
Cluster	ijk	ijk	ijk
Pseudo R^2	0.8827	0.8828	0.8833
Log-likelihood	-4.3198e+12	-4.3156e+12	-4.2959e+12
Nbr.Obs	794161	794161	794161

Table 3.5: Robustness Test of Benchmark Estimation

Regarding other control variables employed in the initial estimations, it can be seen that the fixed effects of η_{jkt} have omitted variables of importing countries at the country-sector-time level. Therefore, corresponding estimates cannot be presented in the results. However, the variables of regional trade agreement and export similarity can still be retained as they measure cross-border relations. From the aspect of results, export similarity continues to show a negative sign at a strong significance level. Moreover, consistent with previous sections, regional trade agreements do not seem to play a significant role in exports.

3.6.2 Alternative Measure of Design Relatedness

In the previous estimation, the level of design-relatedness in exports has been evaluated using the *total relatedness* approach, which measures the level of relatedness at the country-sector level. However, a more precise metric called *relatedness density* has been developed to remove the relatedness associated with designs lacking comparative advantage. This method filters out those designs and only considers effective design-relatedness while standardising the relatedness within a specific area. Therefore, using design-relatedness density instead of mere design-relatedness can perform a robust test to analyse the impact of design capability on export value for exporting countries.

	(1)	(2)	(3)	(4)	(5)
Design Capability$_{ik,t-1}$	0.0929***	0.0952***	0.0903***	0.0912***	0.0938***
	(0.0220)	(0.0220)	(0.0221)	(0.0220)	(0.0221)
Design Comparative Advantage$_{ik,t-1}$	0.1132**	0.1165**	0.1135**	0.1133**	0.0974*
	(0.0398)	(0.0398)	(0.0397)	(0.0400)	(0.0401)
Design Relatedness$_{ik,t-1}$	0.1133***	0.1101***	0.1135***	0.1147***	0.1174***
	(0.0282)	(0.0281)	(0.0281)	(0.0280)	(0.0282)
Design Capability$_{ik,t-1}$ × Design Similarity$_{ijk,t-1}$		-0.0278*			
		(0.0114)			
Design Relatedness$_{ik,t-1}$ × Design Similarity$_{ijk,t-1}$			-0.0871*		
			(0.0424)		
Design Complexity$_{k,t-1}$ × Export Similarity$_{ijk,t-1}$				-0.2213**	
				(0.0789)	
Design Complexity$_{k,t-1}$ × Design Comparative Advantage$_{ijk,t-1}$					0.1006**
					(0.0379)
Design Similarity$_{ijk,t-1}$		0.1329	0.0350		
		(0.0850)	(0.0536)		
Design Complexity$_{k,t-1}$				-0.0213	-0.0697*
				(0.0217)	(0.0275)
Export Similarity$_{ijk,t-1}$	-0.7332***	-0.7255***	-0.7262***	-0.7138***	-0.7298***
	(0.1017)	(0.1015)	(0.1014)	(0.0994)	(0.1015)
Design Capability$_{jk,t-1}$	0.0282*	0.0297*	0.0310*	0.0266	0.0286*
	(0.0143)	(0.0142)	(0.0143)	(0.0143)	(0.0142)
Design Relatedness$_{jk,t-1}$	-0.0282*	-0.0281*	-0.0285*	-0.0271*	-0.0282*
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Design Comparative Advantage$_{jk,t-1}$	0.0748*	0.0740*	0.0725*	0.0717*	0.0701*
	(0.0356)	(0.0357)	(0.0357)	(0.0354)	(0.0354)
Tariff$_{jk,t-1}$	-0.9613**	-0.9555**	-0.9689**	-0.9685**	-0.9628**
	(0.3474)	(0.3474)	(0.3487)	(0.3480)	(0.3471)
Regional Trade Agreement$_{ij,t-1}$	0.0379	0.0495	0.0462	0.0391	0.0467
	(0.0698)	(0.0699)	(0.0696)	(0.0697)	(0.0701)
Constant	19.0695***	19.0373***	19.0662***	19.0886***	19.0656***
	(0.1805)	(0.1823)	(0.1816)	(0.1819)	(0.1842)
Fixed Effect	ij k t	ij k t	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk	ijk	ijk
Pseudo R^2	0.8446	0.8447	0.8447	0.8448	0.8448
Log-likelihood	-5.7217e+12	-5.7181e+12	-5.7186e+12	-5.7164e+12	-5.7171e+12
Nbr.Obs	795410	795410	795410	795410	795410

Table 3.6: Robustness Test with Design Relatedness Density

It can be found from Table (3.6) that replacing the total relatedness with the design relatedness density to capture the design relatedness in exporting countries generates a larger estimated value for the coefficients of design relatedness with the same significance level. It can be concluded that the variable *Design Relatedness* positively affects exports, and this conclusion can pass the robustness test.

Moreover, after replacing the measure of design relatedness, the performance of other variables deserves attention. The variables of *design capability* and *comparative advantage* of exporting countries can be considered to play a positive role in exports. As the corresponding estimations in this robustness test do not tend to change too much along with the change of design relatedness measurement.

As the *design capability*, *design comparative advantage*, and *design relatedness* of exporting countries appear to be as similar as before, the interactive effect can be discussed on this basis. Still, *design similarity* can be thought to play a moderating role in the effect of *design capability* of exporting countries on export, and the effect of *design relatedness* of exporting countries on exports. Due to the negative and significant estimates of interaction term involving *design similarity*.

Furthermore, the estimation on *design complexity* and its interaction terms suggests that *design complexity* has a mediating role in exports. The single variable of *design complexity* does not tend to play a significant role in exports, while its interaction terms are significant for both the effect of export similarity on export value and the effect of the *design comparative advantage* of exporting countries on export value. Export similarity between both parties is considered a barrier in bilateral trade, and this barrier is larger in product sectors with a high level of *design complexity*. On the other hand, the *design comparative advantage* of exporting firms is considered the revealed advantage existing in exporting countries. Therefore, this advantage can be better utilised in product sectors with a high level of *design complexity*. These results are consistent with the primary estimation; hence all hypotheses can pass the robustness test.

The results for other control variables remain consistent with the previous estimation. The *design capability* of importing countries cannot be considered significant in trade as it failed to pass both the primary and robustness tests. Although the *design relatedness* and *design comparative advantage* of importing countries appear statistically significant in this robustness test, since they cannot pass the benchmark estimation, it cannot be concluded that the *design comparative advantage* or *design relatedness* of importing countries play a significant role in trade. Additionally, the estimates for the most favoured nation tariff rate of importing countries are negative and statistically significant in this robustness test while the regional trade agreement remains insignificant.

3.6.3 Alternative Measure of Design Comparative Advantage

Design comparative advantage is simply defined as a dummy, however, it eliminates the precise differences among products and countries. Therefore, replacing the dummy variable by the original measurement formula ($\frac{N_k^{t,i}/\sum_k N_k^{t,i}}{\sum_i N_k^{t,i}/\sum_i \sum_k N_k^{t,i}}$) which defines the *design advantage* dummy allows a more accurate variation embodied in estimation.

As the results presented in Table (3.7), the estimated coefficients of variable *Design Comparative Advantage*$_{ik,t-1}$ suggest that the measure of *design comparative advantage value* can improve the significance level compared with the measure of *design comparative advantage dummy*. Moreover, the estimated coefficients are still positive, while the value of estimates has been increased. Additionally, it can be found that the estimated coefficient of the interaction term of *design complexity* and *design comparative advantage* of exporting countries is slightly higher than the primary estimation as well as the previous robustness test. Therefore, by this robustness test, the effect of *design comparative advantage* of exporting countries tends to be larger than it is estimated in other methods. Besides, the interactive effect of *design complexity* on *design comparative advantage* is likely to be larger than other estimations.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Exports	Exports	Exports	Exports	Exports	Exports
Design Capability$_{ik,t-1}$	0.1034***	0.0720***	0.0739***	0.0690***	0.0702***	0.0739***
	(0.0194)	(0.0208)	(0.0208)	(0.0209)	(0.0208)	(0.0210)
Design Comparative Advantage$_{ik,t-1}$	0.4921***	0.5284***	0.5460***	0.5329***	0.5304***	0.5348***
	(0.0866)	(0.0872)	(0.0869)	(0.0868)	(0.0884)	(0.0879)
Design Relatedness$_{ik,t-1}$		0.1222***	0.1188***	0.1225***	0.1236***	0.1246***
		(0.0283)	(0.0282)	(0.0282)	(0.0280)	(0.0282)
Design Capability$_{ik,t-1}$ $\times$ Design Similarity$_{ijk,t-1}$			-0.0330**			
			(0.0113)			
Design Relatedness$_{ik,t-1}$ $\times$ Design Similarity$_{ijk,t-1}$				-0.0929*		
				(0.0425)		
Design Complexity$_{k,t-1}$ $\times$ Export Similarity$_{ijk,t-1}$					-0.2269**	
					(0.0789)	
Design Complexity$_{k,t-1}$ $\times$ Design Comparative Advantage$_{ijk,t-1}$						0.2355**
						(0.0762)
Design Similarity$_{ijk,t-1}$			0.1573	0.0347		
			(0.0844)	(0.0537)		
Design Complexity$_{k,t-1}$					-0.0139	-0.2303**
					(0.0218)	(0.0727)
Export Similarity$_{ijk,t-1}$	-0.7504***	-0.7323***	-0.7229***	-0.7249***	-0.7128***	-0.7307***
	(0.1009)	(0.1009)	(0.1006)	(0.1004)	(0.0984)	(0.1008)
Design Capability$_{jk,t-1}$	0.0302*	0.0284*	0.0301*	0.0314*	0.0268	0.0283*
	(0.0148)	(0.0143)	(0.0142)	(0.0143)	(0.0143)	(0.0143)
Design Relatedness$_{jk,t-1}$	-0.0308**	-0.0283*	-0.0282*	-0.0287*	-0.0273*	-0.0277*
	(0.0116)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0118)
Design Comparative Advantage$_{jk,t-1}$	0.0711*	0.0728*	0.0717*	0.0702*	0.0704*	0.0698*
	(0.0353)	(0.0352)	(0.0354)	(0.0353)	(0.0350)	(0.0352)
Tariff$_{jk,t-1}$	-0.9232**	-0.9685**	-0.9609**	-0.9764**	-0.9747**	-0.9684**
	(0.3452)	(0.3469)	(0.3470)	(0.3482)	(0.3475)	(0.3464)
Regional Trade Agreement$_{ij,t-1}$	0.0559	0.0370	0.0506	0.0461	0.0386	0.0486
	(0.0673)	(0.0687)	(0.0687)	(0.0685)	(0.0686)	(0.0705)
Constant	18.7231***	18.7947***	18.7480***	18.7898***	18.8112***	18.7700***
	(0.1878)	(0.1854)	(0.1876)	(0.1866)	(0.1875)	(0.1917)
Fixed Effect	ij k t	ij k t	ij k t	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk		ijk	ijk
Pseudo R^2	0.8448	0.8452	0.8454	0.8453	0.8454	0.8454
Log-likelihood	-5.7150e+12	-5.6993e+12	-5.6943e+12	-5.6958e+12	-5.6939e+12	-5.6951e+12
Nbr.Obs	795410	795410	795410	795410	795410	795410

Table 3.7: Robustness Test with Definition Measurement of Design Comparative Advantage

For variables including *design capability* and *design relatedness* in exporting countries, both their positive effects and significance level can pass this robustness test. Moreover, the moderating effect of *design similarity* on *design capability* and *design relatedness* keeps the significance level as before. Furthermore, the mediating effect of *design complexity* on *export similarity* and *design comparative advantage* retains the previous performance as well as the significance level.

3.6.4 Coefficient Analysis

This section aims to summarise the estimated coefficients of variables, including the baseline estimation, interactive effect, and the robustness test. Using estimates and their corresponding standard errors, the confidence interval can be calculated at a 95% significance level. The effect of industrial design on exports can be presented in error-bar charts.

3.6.4.1 Design Capability

As can be seen in Figure (3.10), the effect of *design capability* of exporting countries on exports can be said to be statistically significant and positive at the 95% confidence interval. Taking into consideration the standard errors of estimates, this positive effect holds in the interval [0.028, 0.169] (the estimated coefficient takes possible values in this closed interval). Of note is that if the *design comparative advantage* is measured numerically instead of with dummy indicators, the effect of *design capability* is lower than in other estimations. To some extent, it can be said that the effects of *design comparative advantage* and *design capability* of exporting countries have an intersection, such that the effect of *design comparative advantage* can be increased along with the correction on measurement, while the effect of *design capability* is decreasing. This point of view warrants further discussion with an analysis of the estimation of *design comparative advantage*.

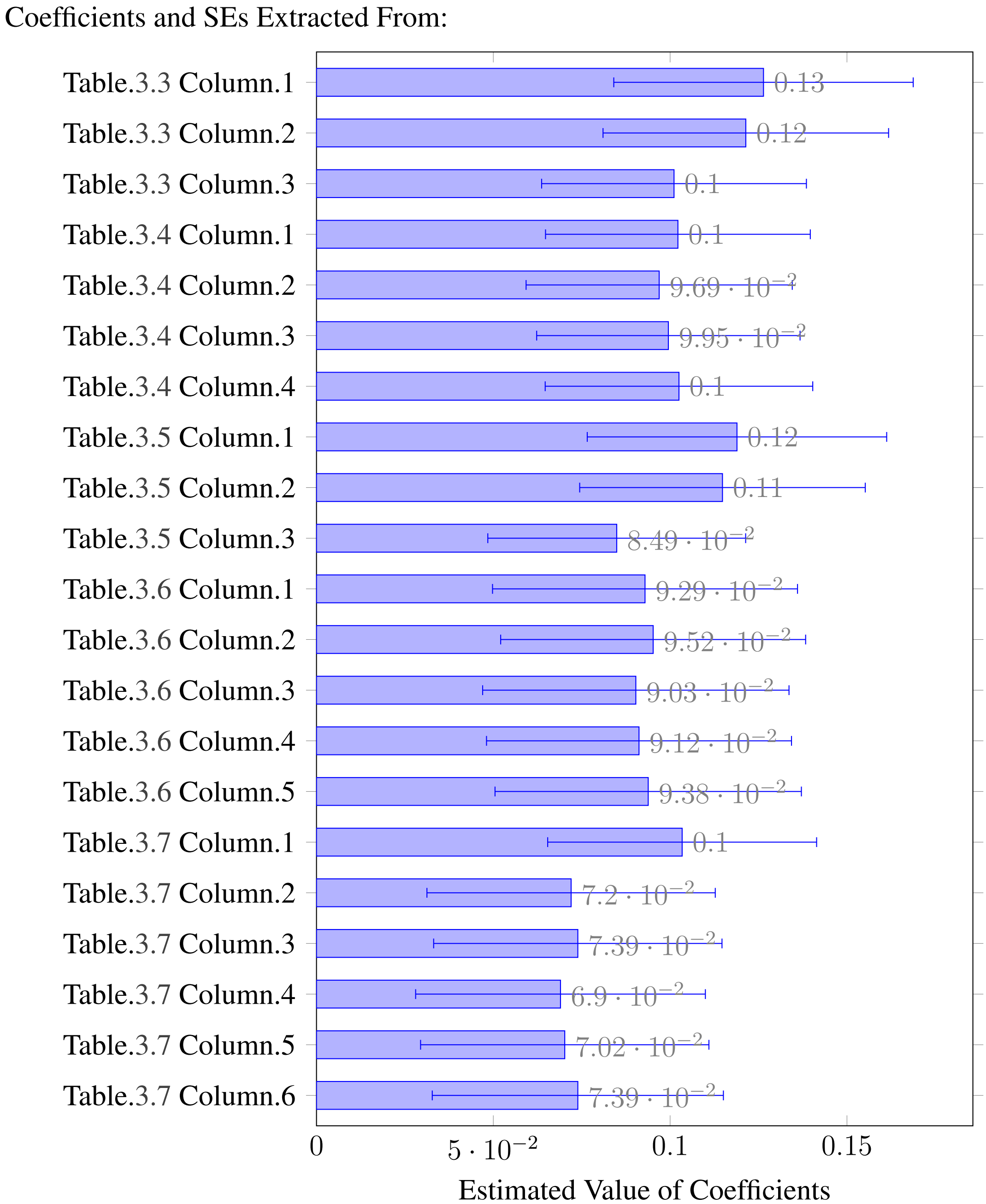


Figure 3.10: Estimated Coefficients of Design Capability

3.6.4.2 Design Comparative Advantage

Design comparative advantage of exporting countries tends to have a positive effect on exports, as suggested by the estimations presented in Figure (3.11). At the significance level of 95%, the confidence interval of estimated coefficients remains positive. However, when the *design comparative advantage* is measured using a definition formula with numeric values allowing for accurate variations, its effect on exports appears to be larger than when it is measured using a dummy variable. This also shows that *design comparative advantage* can affect the estimated effect of *design capability* on exports, from the perspective of measurement. If its variation can be accurately captured, the effect of *design capability* measured by design count seems to be smaller.

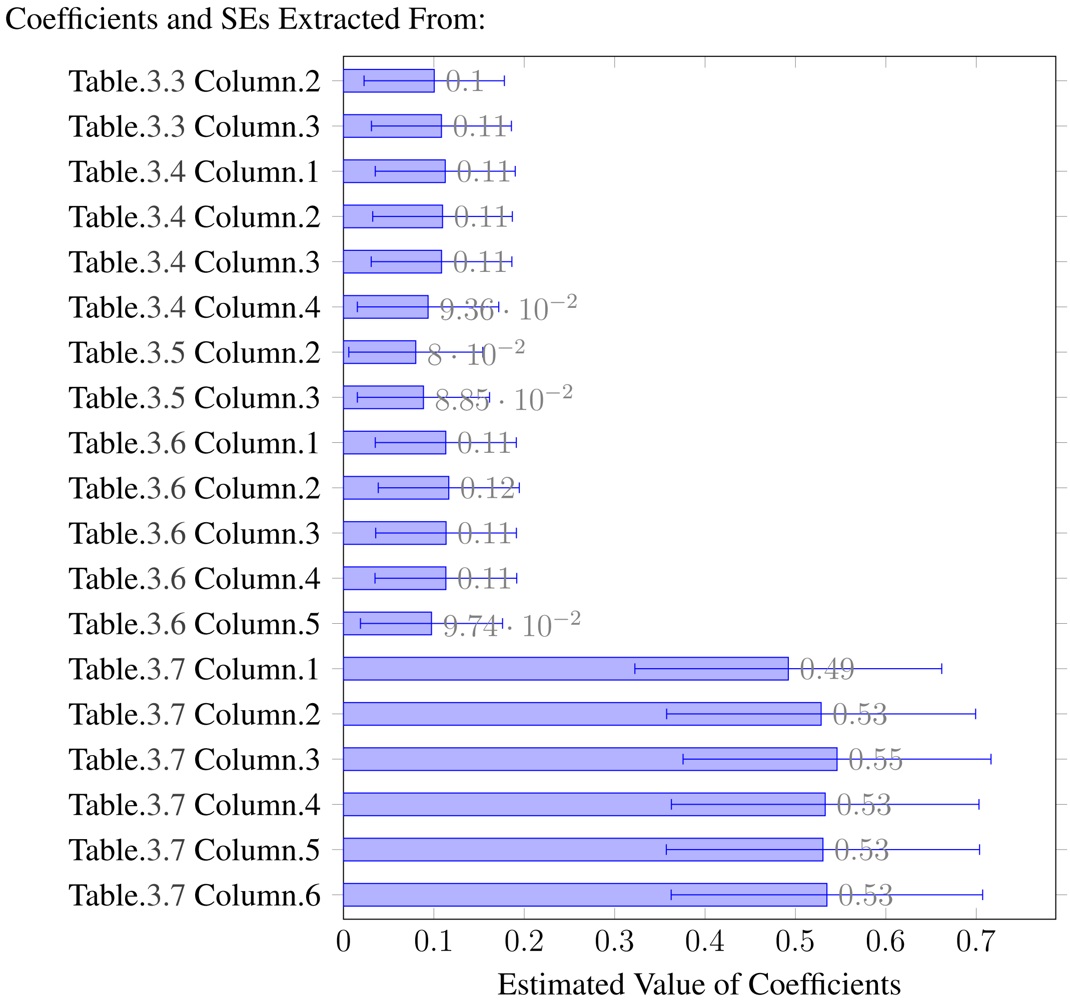


Figure 3.11: Estimated Coefficients of Design Comparative advantages

3.6.4.3 Design Relatedness

According to the estimates in Figure (3.12), the effect of *design relatedness* can be evidenced to be statistically significant and positive in the confidence interval of [0.032756, 0.179872] at the significance level of 95%. This effect is estimated to be higher in robustness test. The estimates of *design relatedness* of exporting countries suggest that the knowledge relatedness in terms of design which is existing in exporting countries can positively affect exports, while unlike the effect of *design capability* on exports, this effect is not likely to be affected by *design comparative advantage*.

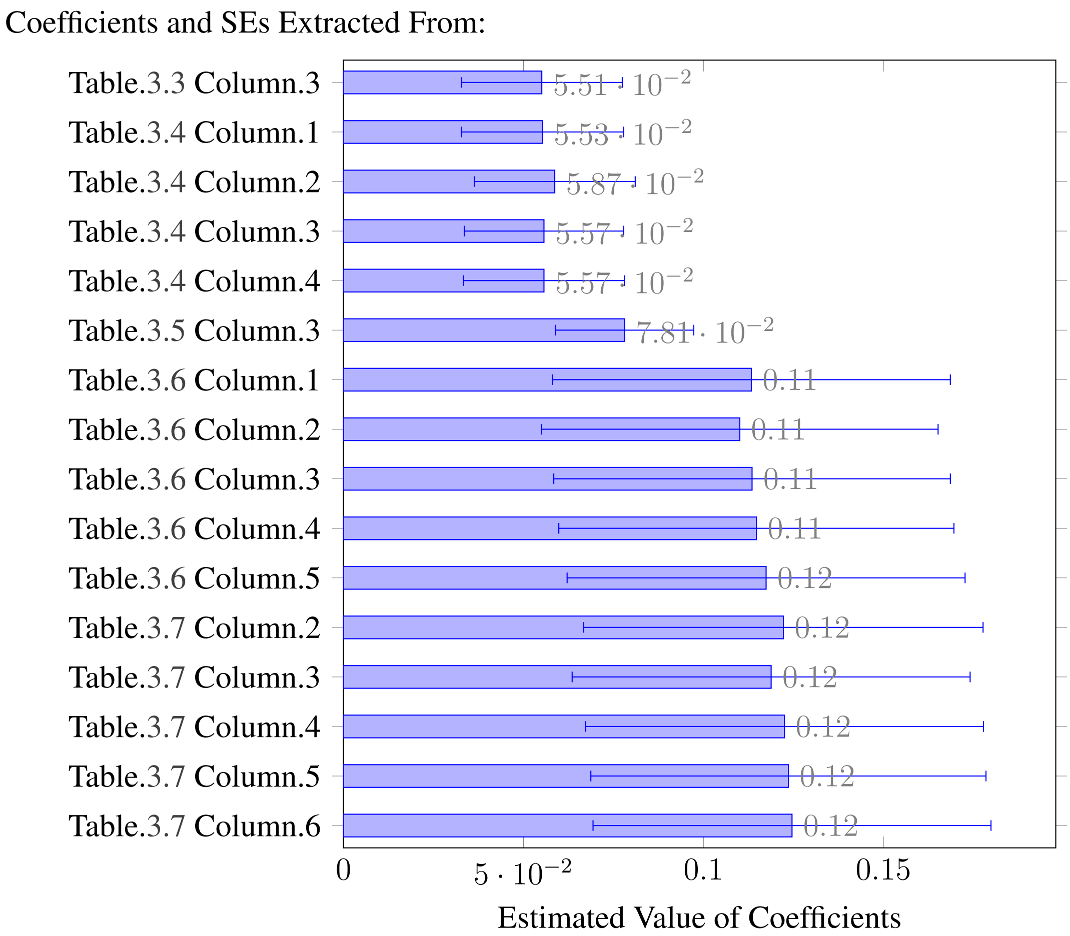


Figure 3.12: Estimated Coefficients of Design Relatedness

3.6.4.4 Design Similarity

Design similarity is likely to have a negative effect on the positive impact of *design capability* of exporting countries on the export value. This mediating effect can be empirically evidenced at a confidence interval of [-0.055148, -0.005456], with a significance level of 95% (see Figure (3.13) for the summarised estimates of the interaction between *design similarity* and exporting country *design capability*). Nonetheless, *design similarity* can be argued to play a moderating role in exports only if it can be proven that the *design capability* of exporting countries has a positive effect on exports. This condition holds true in this study as presented in Figure (3.10); in various regressions, the estimated effect of *design capability* remains statistically positive.

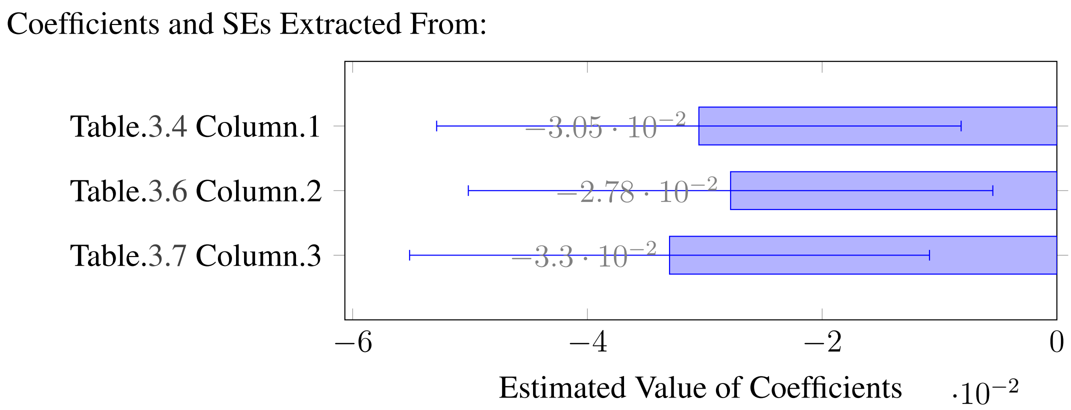


Figure 3.13: Estimated Coefficients of Design Capability × Design Similarity

Based on the similar logic of the interactive effect with *design capability* of exporting countries, *design similarity* is seen to have a moderating role when *design relatedness* of exporting countries has a positive effect on exports. This is illustrated in Figure (3.14), wherein the estimation of interaction term is found to be significantly negative in the 95% confidence interval of [-0.1762, -0.003996]. The interactive effect between *design similarity* and *design relatedness* appears to be significantly negative, which can be discussed in tandem with the estimated effect of *design relatedness* of exporting countries as shown in Figure (3.12). As the significant and positive role of *design relatedness* on exports has been established, it can be argued that *design similarity* between bilateral trade countries can weaken the promoting effect of *design relatedness* of exporting countries.

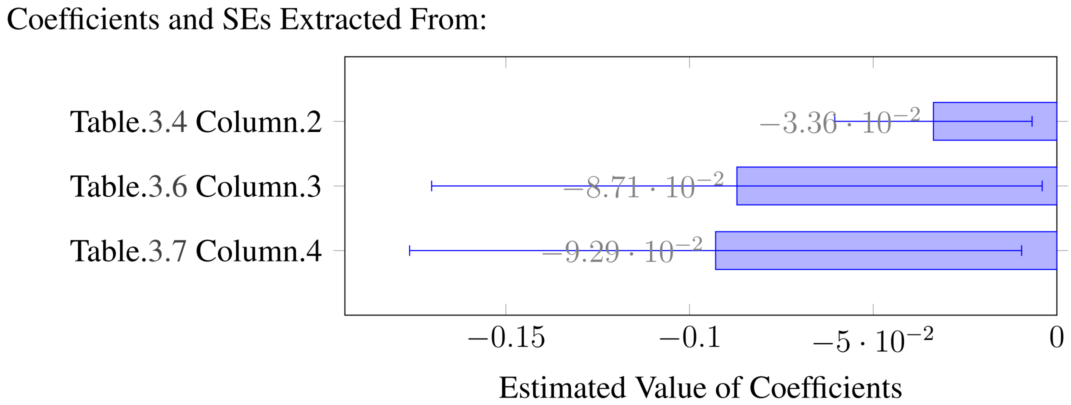


Figure 3.14: Estimated Coefficients of Design Relatedness × Design Similarity

3.6.4.5 Design Compleixty

The indirect effect of *design complexity* on exports can be shown in Figure (3.15). It plays a significant role via its mediating effect on export similarity. Then, the mediating effect will be delivered when the exports change along with the change of similarity of export structure in bilateral countries. According to the basic estimation on interactive effect and the robustness test, the effect of *design complexity* on export similarity tends to be negatively significant within the interval [-0.382, -0.066]. Since export similarity plays a negative role in trade, which is regarded as a friction effect to some extent. Thus, according to the estimation results, this friction could be larger in product sectors with high *design complexity*.

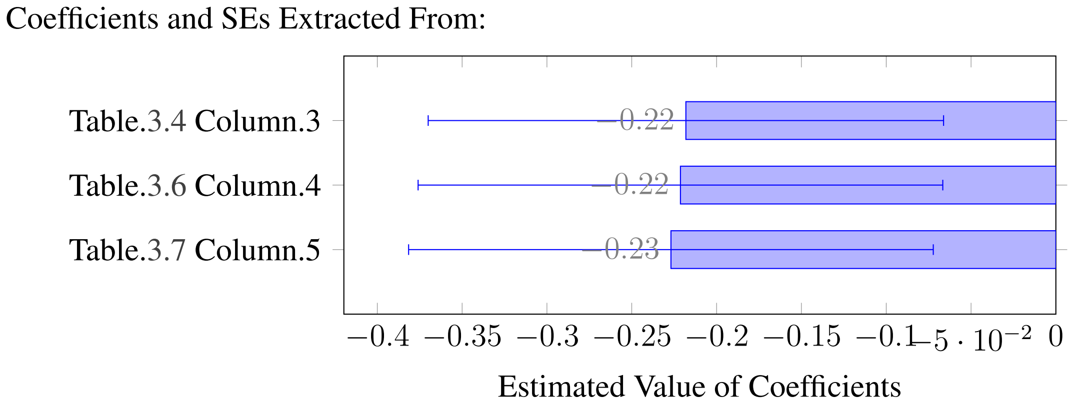


Figure 3.15: Estimated Coefficients of Design Complexity × Export Similarity

As has been discussed, the sectoral *design complexity* has a positive effect on the *design comparative advantage* of exporting countries. This means that countries can capitalise on their advantage more effectively in sectors with high *design complexity* compared to those with low complexity. The effect of *design complexity* does not directly affect exports; it instead serves to amplify the existing advantage of exporting countries. As seen in Figure (3.16), this positive mediating effect is significant within the 95% confidence interval of [0.018, 0.385]. Moreover, the effect seems to be much higher when measured numerically than when simply indicating whether or not countries have a *design comparative advantage*. This can be seen from the extremely high estimated effect in Table (3.7) compared to other estimation results. Nevertheless, if measuring *design comparative advantage* numerically, the estimated coefficient of the single variable is also higher than when using a dummy. Thus, the interactive effect becomes larger as the estimation of the single variable changes, though it cannot be said that the interactive effect necessarily increases.

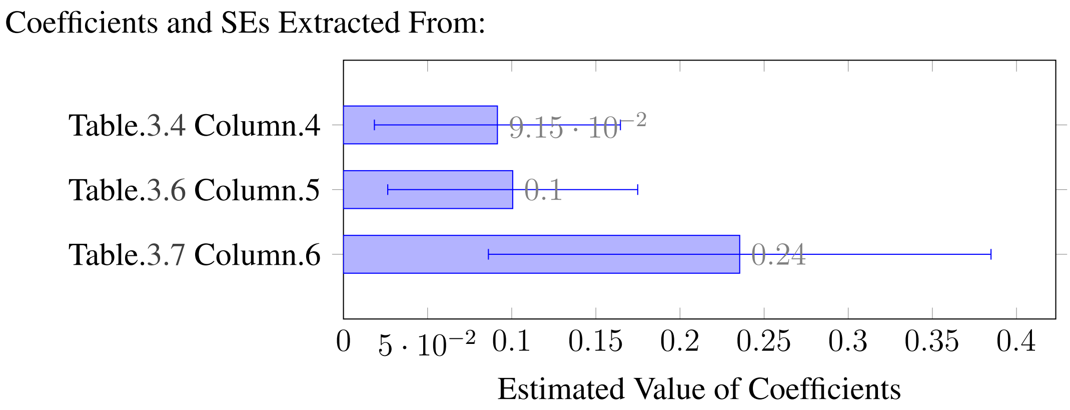


Figure 3.16: Estimated Coefficients of Design Complexity × Design Comparative Advantage

3.6.4.6 Summary of Coefficient Analysis

In summary, the primary estimation proposed in the methodology section and the robustness test demonstrate that *design components* can be empirically evidenced to have a significant role in trade. This effect is seen on the trade value from various perspectives; *design capability*, *design comparative advantage*, and *design relatedness* in exporting countries play a promoting role in exports. These factors can be considered to directly impact trade, implying that design functions as a driver of exporting competitiveness, which brings an increase of export value.

Furthermore, due to the direct impact of design being evidenced, it can also be argued that *design similarity* and *design complexity* can act as moderators of exports. The *design similarity* captures how similar both countries' knowledge structures are with regards to design, thus playing a negative role in the effect of *design capability* and *design comparative advantage* of exporting countries on exports. *Design complexity* is likely to amplify the existing *design comparative advantage* and the negative effect from export similarity on bilateral trade. Therefore, this suggests that in product sectors with higher *design complexity*, the promoting effect of existing design advantages of exporting countries on exports would be greater, while the friction effect of export similarity is also amplified.

3.7 Discussion

Design innovation has been recognised as a crucial driver of economic growth and competitiveness. However, the role of design in promoting exports at the national level has been largely overlooked in existing research. This study aims to fill this gap by investigating the impact of design on exports using design patent data. Specifically, this study examines the effects of *design capability*, *design comparative advantage*, *design relatedness*, *design similarity*, and *design complexity* on exports.

The findings of this study suggest that *design capability*, *design comparative advantage*, and *design relatedness* have a positive and significant impact on exports. *Design similarity*, on the other hand, has a negative impact on exports, while *design complexity* has a mediating effect on the relationship between *design comparative advantage* and exports, as well as the relationship between export structure similarity and exports.

This study contributes to the literature by providing empirical evidence on the promoting effect of design on exports at the national level. Moreover, this study introduces new variables, such as *design comparative advantage*, *design relatedness*, *design similarity*, and *design complexity*, to capture the different aspects of design innovation and their impact on exports. The findings of this study can inform policymakers and firms on the importance of design innovation in promoting exports and enhancing competitiveness in the global market.

3.7.1 Design Capability

The *design capability* of exporting countries is argued to play a significant role in promoting bilateral trade, and this finding is supported by both initial estimations and robustness tests in this study. The sectoral bilateral level estimation provides evidence that design is an essential ability that enables economies to seek competitiveness in globalisation and international trade. This finding contributes to the current literature from various perspectives, including the drivers of exports at the country level, innovation-driven growth, and empirical applications of design patent data at the sectoral level.

Product innovation has been shown to encourage non-exporting firms to enter the international trade market (Cassiman, Golovko & Martínez-Ros, 2010). Furthermore, the importance of product design in product differentiation strategies has been highlighted (Blazeska & Ristovska, 2016). However, current research on design is focused on product development and cost management, which encourage firm growth (Calantone, Tamer-Cavusgil et al., 2004). In addition to these findings, which discuss design innovation from a firm perspective, this study provides the first evidence that design can promote a country's exports. This promoting effect is direct and significant.

Furthermore, this study delves into the realm of design-driven growth, a topic that has been largely overlooked in existing research (Broughel & Thierer, 2019; Christensen et al., 2018). While innovation-driven growth has been extensively discussed in academic papers, the role of design in driving growth has been a significant gap in the literature. This study aims to fill this gap by investigating the impact of design on exports. While a considerable body of literature has focused on R&D as a driver of firm exports (Falk & de Lemos, 2019; Leung & Sharma, 2021), it fails to capture the extent to which innovation outcomes can promote growth. To address this limitation, this study employs design patent data to measure both innovation outcomes and capabilities, as suggested by current research (Quatraro, 2009; ter Haar, 2018).

The *design capability* can be measured as a volume using design patent data (Song & Ma, 2022), which directly captures the design outcomes. This approach has been explored in previous studies on innovation (Bottazzi & Peri, 2003; Katila, 2000; Nagaoka et al., 2010), and using registered designs or design patent data is another viable option for researching economic growth. It is important to note that this application of design patent data is at the sectoral level, and the correspondence between design classification and industry classification allows for future research to investigate design data at this level.

In conclusion, the discovery that the *design capability* of exporting countries can influence their export value helps to address the issue of design-driven growth at the national level. Additionally, by utilising design patent data to measure design capability, this research complements previous studies that have used patent data to measure innovation outputs. Moreover, to analyse design capability at the sectoral level, this study involved converting classifications between industrial design and product sectors, paving the way for future sector-specific research using design patent data.

3.7.2 Design Comparative Advantage

According to the results and robustness tests, the *design comparative advantage* of exporting countries can have a positive impact on their corresponding export value. This finding adds to the previous discovery that *design capability* plays a crucial role in exports. *Design comparative advantage* directly measures the competitiveness of exporting countries in terms of design innovation in the global market. Therefore, this finding contributes to the literature on the competitiveness of economies in globalisation from two perspectives. Firstly, *design comparative advantage* is the first measure of economies' global competitiveness in terms of design innovation. Secondly, compared to *design capability*, *design comparative advantage* eliminates the impact of economy size on exports.

This study highlights the importance of design innovation in the global market and its impact on the competitiveness of economies. The findings suggest that countries with a strong *design comparative advantage* are likely to have a higher export value, regardless of their size. Policymakers and businesses should focus on developing *design comparative advantage* to enhance their competitiveness in the global market.

This research is the first to propose the *design comparative advantage* (DCA) in the context of design innovation. Following Balland, Boschma, Crespo, and Rigby (2019) who have employed RCA to measure revealed technological advantage (RTA), *design comparative advantage* captures the design competitiveness of economies.

Revealed comparative advantage is a widely used indicator for measuring export competitiveness (Laursen, 2015). It has been extensively employed in empirical research to evaluate the ability of economies to compete in the global market (Abbas & Waheed, 2017; Saki et al., 2019; Serin & Civan, 2008; Singh et al., 2020). Furthermore, this measurement has been applied to innovation research, specifically *revealed technological advantage* (RTA), which captures the comparative advantage of economies or firms in terms of technologies (Balland, Boschma et al., 2019; Cantwell, 2001; Le Bas

& Sierra, 2002). Therefore, the variable construction of DCA contributes to existing research from the perspective of the empirical application of RCA to design innovation.

Unlike *design capability*, which is regarded as promoting exports by increasing the competitiveness of economies, the finding related to *design comparative advantage* is directly focused on the effect of design competitiveness on exports. Employing regional-level data, D'Adda et al. (2019) suggests that the innovation index is often associated with the economys size. While *revealed comparative advantage* is considered to remove the impact of economies of scale (Faustino, 2008). The measure of *design comparative advantage* employed the construction method of RCA; thus, it can remove the impact of economies of scale from both sectoral and national aspects.

Recent research has revealed that innovation can enhance global competitiveness for both countries and firms (Chung, 2011). However, the direct impact of innovation competitiveness on exports has not been thoroughly explored. This study aims to fill this gap by demonstrating that innovation competitiveness directly improves exports, specifically from a design perspective. Additionally, the use of *design comparative advantage* as a measure can eliminate the influence of economies of scale. This study is also the first to apply *revealed comparative advantage* to design innovation.

3.7.3 Design Relatedness

This study reveals that the similarity of design capabilities between economies can positively impact their corresponding exports. This conclusion has been supported by both primary estimations and robustness tests. In addition to exploring *design capability* and *comparative advantage*, this study highlights the significance of *design relatedness* in exports, which is essentially the role of design knowledge space in exports. Therefore, the findings related to *design relatedness* can contribute to the existing literature in the following ways: (i) This study is the first to apply knowledge space to design innovation; (ii) The empirical evidence presented in this study sheds light on the relationship between design knowledge relatedness and exports, highlighting the promoting effect of related design knowledge on exports.

The concept of *design relatedness*, which includes variables such as *total design relatedness* and *design relatedness density*, represents the first application of economic complexity theory in the context of design innovation. This theory was originally proposed by Hidalgo, Klinger et al. (2007) to investigate regional growth using international trade data, but has since been widely adopted in innovation research (Balland & Rigby, 2017; Pugliese et al., 2019). While previous research has focused on patent data to capture technological innovation, design patent data has a similar structure, making it possible to apply economic complexity theory to industrial designs.

This study is unique in that it captures the design space at both the country and product-sectoral levels, making it the first of its kind. Additionally, knowledge relatedness is measured using design patent data, allowing for the capture of the knowledge space (Kogler et al., 2013; Vlčková et al., 2018). While previous studies, such as Kogler et al. (2013), have used patent data to identify regional knowledge space, this study focuses on design knowledge space. Furthermore, Balland, Boschma et al. (2019) have used a revised probabilistic method to estimate technological relatedness, which has inspired the construction of design relatedness in this study. Overall, this study fills a gap in research regarding design knowledge space.

As it can be argued that design knowledge relatedness plays a significant and positive role in exports, there is empirical evidence to support the notion that knowledge relatedness can promote exports from a design perspective. Previous research has explored the role of knowledge relatedness or knowledge space in regional growth (Boschma R. A. & Frenken, 2011; Innocenti & Lazzeretti, 2019; Sapienza et al., 2004). However, there is a lack of literature describing the role of design knowledge relatedness in economic growth. The findings of this study explore the design drivers of exports from the perspective of a knowledge-based economy.

The studys calculation of *design relatedness* is conducted at the product-sectoral level. As a result, the empirical findings regarding the correlation between *design relatedness* and exports can provide valuable insights into sectoral research that is pertinent to bilateral trade. Jun et al. (n.d.) suggest that product relatedness can enhance bilateral trade, and the sectoral estimation of design and exports can supplement the analysis of sectoral bilateral relatedness. Therefore, this study's findings can contribute to a more comprehensive understanding of the relationship between design and bilateral trade.

In summary, this study provides empirical evidence for the promoting role of *design relatedness* in exports. The study draws on the application of economic complexity theory, which can complement existing research in this area. Furthermore, the study goes beyond current research on design sectors and exports (Design Council, 2018) by examining knowledge relatedness and knowledge space in the context of design. By discussing *design relatedness* as a driver of exports, the study contributes to the research on export drivers.

3.7.4 Design Similarity

Design similarity is a crucial variable that evaluates the extent to which the design knowledge structures of two different countries are similar to each other. This study is the first to propose this variable, which enables the comparison of knowledge spaces of different territories. This measure is not only useful for design innovation but also for capturing the similarity of knowledge space. The results of this study suggest that design similarity weakens the positive effect of design capabilities and design relatedness of countries on exports. Therefore, this finding can contribute to research on the moderating factors affecting exports.

Furthermore, the importance of design similarity cannot be overstated. It is a critical factor that affects the success of exports and innovation in design. This study provides valuable insights into the role of design similarity in international trade and highlights the need for further research in this area. By understanding the impact of design similarity, policymakers and businesses can make informed decisions that will help them succeed in the global marketplace.

Current research has introduced the concept of design similarity from a micro perspective (de Angelis et al., 2017). This perspective focuses on product similarity and customer preference. However, existing papers have already addressed product differentiation (Boehe & Barin Cruz, 2010; Inui et al., 2017), which is achieved through design (Doyle & Broadbridge, 1999; Reimann & Schilke, 2011). Therefore, design similarity, which is calculated at the product-sectoral level, can be used to explore product differentiation between different countries. It should be noted that design similarity is not a direct measure of product differentiation and is not expected to play a direct role in exports.

Countries that share high export similarity often face strong competition in the global market, as noted by D'Adda et al. (2019). However, design similarity does not directly hinder bilateral trade. Instead, it is believed to impact exports by moderating the promoting effect of design capability and relatedness.

The impact of innovation on exports has been a topic of discussion in recent papers, with a focus on the moderating effect of firm characteristics. According to Villar et al. (2012), the role of firm characteristics in the relationship between innovation and exports is significant. However, when considering regional or national analysis, the moderating effect of firm characteristics can be explained by economies of scale. Moreira et al. (2022) also highlights the moderating effect of government support and internationalisation on innovation capabilities and exports. However, policy factors can also directly explain regional exports.

Research has shown that the connection between exporters and importers is influenced by the similarity in values and culture (D.-.-J. Lee et al., 2007). The similarity in design, as measured by design knowledge relatedness, can partially capture the similarity in knowledge value. This approach specifically emphasises the design aspect and the impact of innovation on exports.

The findings of the research indicate that design similarity does not act as a direct obstacle to bilateral trade. However, it does impact the innovation factors of countries. The study also reveals that the effect of design capabilities on exports is moderated by design similarity. This means that if two countries have a high degree of similarity in terms of design knowledge, the impact of design capability on exports is likely to be less significant. Additionally, the research suggests that knowledge relatedness of design does not have a strongly positive influence on exports, as compared to countries with a low level of design similarity.

3.7.5 Design Complexity

This research reveals that the complexity of design plays a crucial role in exports by influencing the positive impact of a country's design comparative advantage and the negative impact of export structure similarity. This study is the first of its kind to explore the similarity of knowledge structure in the realm of design innovation. Furthermore, it provides empirical evidence that design similarity plays a significant mediating role in exports.

The Design Complexity Index is a groundbreaking application of economic complexity theory to design patent data. This theory has been extensively used in empirical research related to economic growth (Hidalgo, 2021). It can also be applied to measure knowledge diffusion in the context of bilateral trade (Jun et al., n.d.), and to investigate smart specialisation and regional growth in innovation research (Balland, Boschma et al., 2019).

In addition to the contribution on empirical application of economic complexity, design complexity can also contribute to the innovation research from the theory perspective. Following the technology complexity index proposed by Balland, Boschma et al. (2019), the design complexity is constructed to capture the product complexity from the design perspective. As it has been discussed that technology complexity results in the risk when a type of technologies is entering a new market, design complexity is considered to negatively affect the innovation advantage of countries. The finding is consistent with this expectation, which suggests that design complexity can enhance the design comparative advantage of exporting countries.

Incorporating design complexity into innovation research can provide a more comprehensive understanding of the factors that contribute to a country's innovation advantage. By considering both economic and design complexity, policymakers and businesses can make more informed decisions about how to promote innovation and competitiveness in their respective industries.

In addition to the practical application of economic complexity, theoretical research on innovation can also benefit from the consideration of design complexity. Drawing on the technology complexity index introduced by Balland, Boschma et al. (2019), design complexity can be used to measure product complexity from a design standpoint. As previously discussed, technology complexity can pose risks when new technologies are introduced to a market, and similarly, design complexity is believed to have a negative impact on a country's innovation advantage. However, the results of the study suggest that design complexity can actually enhance the positive effects of a country's comparative advantage in design-related exports, which is in line with expectations.

This study contributes to the existing literature on the factors that influence export similarity. Previous research by Bahar et al. (2014) has identified the impact of geographic, economic, and cultural proximity on export similarity between countries. However, this study adds a new dimension by highlighting the role of design complexity in determining export similarity, particularly in terms of design innovation.

Furthermore, this study demonstrates the interactive effect between design complexity and export similarity, which can have a significant impact on bilateral trade. In contrast to the interaction effect between design complexity and design comparative advantage, design complexity can also amplify the negative effect of export similarity. Therefore, it is crucial to consider the role of design complexity in bilateral trade and its potential impact on export similarity.

Besides, this research sheds light on the importance of various factors in determining export similarity between countries. It also highlights the need to consider the interactive effect of design complexity and export similarity in bilateral trade. By doing so, policymakers and businesses can make informed decisions that can lead to more successful trade relationships.

3.8 Conclusion

In conclusion, this study has shed light on the crucial role of industrial design in promoting exports and enhancing the competitiveness of economies in the global market. By utilising design patent data, this research has provided a unique perspective on measuring design capability, design comparative advantage, design relatedness, design similarity, and design complexity. These variables have been shown to have significant impacts on exports, both individually and interactively.

The findings of this study have important implications for policymakers and businesses. They highlight the need to focus on developing design capability and comparative advantage to enhance competitiveness in the global market. Additionally, the study emphasises the importance of considering design relatedness and similarity in bilateral trade relationships. Finally, the study underscores the need to consider the complexity of design in innovation research and its potential impact on export similarity.

Overall, this research has contributed to the literature on the role of industrial design as part of innovation in economic growth and competitiveness. It has also demonstrated the potential of design patent data as a valuable source for measuring design-related variables. Future research can build on these findings by exploring the impact of industrial design on other aspects of economic growth and by investigating design-related variables at the sectoral level.

Chapter 4

Interdependencies of Industrial Deisgn and Exports: Using UK Regional Data and Panel VAR

4.1 Introduction

The concept of the design economy, proposed by Heskett (2017), emphasises that design is not only a tool for product development but also a source of value-added for goods and services, contributing to sustainable growth. In the UK, the creative industries, including the design sector, have made significant contributions to the gross value added (Cunningham and Bakhshi, 2008; Design Council, 2016). Over the past 30 years, the UK design economy has evolved from a focus on industrial design and the use of new technologies to a broader conceptual framework encompassing problem-solving in various fields through design thinking (Q. Sun, 2010). Design is now seen as an industry that supplies creative ideas and works across traditional sectors, with its importance in promoting social and economic development being emphasised (T. Love, 2007).

Furthermore, aside from the significance of design sectors or industries, research has shown that design plays a crucial role in promoting innovation (Kembaren et al., 2014) and driving exports in the UK (Design Council, 2016, 2018). The advanced level of design development in the UK leads to several outcomes: (i) the creation of innovative and high-quality products and services that are appealing in the global market (Crilly et al., 2004), (ii) the production of goods that possess a high level of adaptability and differentiation in foreign markets (Afrifa et al., 2018; Larimo and Kontkanen, 2008), and (iii) the cultivation of strong design capabilities within firms, enabling them to adjust their market strategies and gain a competitive advantage in the global market (Kaleka, 2002).

On the other hand, the motivating role of exports in design registration is complex and not as directly evident in empirical research compared to the promoting role of industrial design in exports. However, papers often mention exports as a motivation for firms to seek patent protection overseas (Milesi et al., 2022; P. J. Smith, 2001).

Theoretical explanations suggest that exporters consider industrial design protection in destination countries to avoid legal disputes and facilitate business activities (Dachs and Pyka, 2010). Additionally, exporting firms find business opportunities and expand their knowledge capital in foreign markets (Shu and Steinwender, 2019). Furthermore, exporters register designs overseas to optimise distribution, packaging, or manufacturing activities (WIPO, 2006). These reasons, supported by relevant theoretical evidence, highlight the potential influence of exports on overseas industrial design registration (Awokuse and Gu, 2015; Canals and Şener, 2014; Liang and Xue, 2010).

The examination of the interrelationship between industrial design and exports holds significant scholarly importance for several reasons. Firstly, while existing research has widely established the promoting role of industrial design in exports (J. H. Love and Roper, 2015), there remains a relative dearth of empirical research exploring the motivating role of exports in design registration. By addressing this research question, we aim to fill this empirical gap and contribute to a deeper understanding of the complex dynamics between exports and industrial design (Milesi et al., 2022; P. J. Smith, 2001). Secondly, theoretical explanations suggest that exports can serve as a driving force for firms to seek patent protection overseas, expand their knowledge capital, and optimise distribution and manufacturing activities (Dachs and Pyka, 2010; Shu and Steinwender, 2019; WIPO, 2006). By empirically investigating these theoretical assertions, we can provide valuable insights into the motivations underlying overseas industrial design registration (Awokuse and Gu, 2015; Canals and Şener, 2014; Liang and Xue, 2010). Consequently, this research question contributes to the advancement of both theoretical and practical understanding in the field.

The research question is addressed in this study through the utilisation of design data obtained from Questel IP. The trade data, sourced from the website UK Trade Info[1], is maintained and managed by HM Revenue & Customs (HMRC). The interdependencies between industrial design and exports are investigated using the Panel Vector Autoregression (PVAR) approach. Valuable insights into the patterns and trends of design registration are derived from the design data obtained from Questel IP, while the trade data provides significant information on export dynamics. Through the PVAR analysis, the temporal dynamics and causal relationships between industrial design registration and exports are explored, shedding light on the underlying mechanisms that drive this interrelationship. By incorporating these datasets and employing the PVAR approach, this research aims to provide empirical evidence and contribute to a rigorous and systematic understanding of the interplay between industrial design and exports.

The research findings suggest that there exist interdependencies between overseas design registration and exports from two perspectives: the interdependencies between overseas design registration and exports, and the interdependencies between overseas design relatedness and exports. These interdependencies are found to be positive. How-

[1] https://www.uktradeinfo.com/

ever, in terms of influence, it is observed that overseas design registration is more encouraged by the existing overseas design relatedness compared to exports. Similarly, the existing design registrations generated in the overseas market have a greater impact on improving exports compared to the existing design relatedness. Furthermore, the generation of overseas design relatedness is found to be more driven by the number of overseas design registrations compared to the past value of exports. These findings highlight the intricate and mutually reinforcing relationship between overseas design registration and exports, emphasising the importance of design-related factors in promoting international trade.

This chapter provides an analysis of the interrelationship between industrial design and exports. The conceptual framework establishes the significance of industrial design in driving exports and the reciprocal role of exports in motivating design registration. The study utilises data from Questel IP and UKTRADEINFO to examine overseas design registration, design relatedness, and exports. Methodologically, the research employs the Panel Vector Autoregression (PVAR) model to investigate the temporal dynamics and causal relationships between the variables. The results shed light on the positive interdependencies between overseas design registration and exports, as well as between design relatedness and exports. The discussion section delves into the implications of these findings, synthesising theoretical explanations and empirical evidence to provide a comprehensive understanding of the interplay between industrial design and exports. Finally, the conclusion summarises the key findings and underscores the importance of design-related factors in enhancing international trade.

4.2 Conceptual Framework

The conceptual framework of this section focuses on the interrelationship between industrial design and exports in the UK. It begins by providing an overview of the intangible economy in the UK, highlighting the increasing significance of intangible assets and their impact on long-term growth and regional specialization. The importance of design in the UK economy is then discussed, emphasising its role as a driver of value-added goods and services and its contribution to the gross value added in the creative industries.

The framework further explores the relationship between design and exports, highlighting the promoting role of design in innovation and its ability to drive exports. It is argued that design can make products more attractive, adaptable, and competitive in the global market, leading to increased export performance. The motivating role of exports in design registration is also discussed, suggesting that exporters seek overseas design protection to prevent imitation, expand their knowledge capital, and optimise their production and distribution activities in foreign markets.

The framework extends to the relationship between design relatedness and exports, drawing on the economic complexity theory and its application to knowledge complexity. It is argued that design relatedness, measured by the probability of designs being registered in different classes simultaneously, can drive exports by promoting regional specialisation, innovation, and knowledge diversification. The reverse relationship is also explored, suggesting that exports can drive design relatedness by exposing firms to new technologies and business opportunities in foreign markets.

Finally, this section examines the interrelationship between overseas design registration, design relatedness, and exports. It is argued that overseas design registration can drive exports by providing legal protection, enhancing product innovation, and building reputation in foreign markets. Conversely, exports can drive overseas design registration by creating business opportunities, expanding knowledge capital, and facilitating production and distribution activities. The interrelationship between overseas design registration and design relatedness is also discussed, suggesting a positive correlation between the quantity of design registration and the density of design relatedness.

To investigate these interrelationships, the research question is proposed: *Is there mutual causality existing in the UK exports, the design quantity registered by the UK holders in the overseas market, and corresponding design relatedness generated*? The panel vector autoregression (PVAR) model is proposed as an appropriate method to analyse the interdependencies among these variables. The empirical application of the PVAR model in previous research is reviewed, highlighting its suitability for investigating the relationship between design and exports.

In summary, this conceptual framework provides a comprehensive understanding of the interrelationship between industrial design and exports in the UK. It highlights the importance of design in the intangible economy, explores the promoting and motivating roles of design in exports, and discusses the relationship between design relatedness and exports. The framework also proposes a research question and the application of the PVAR model to investigate the mutual causality among overseas design registration, design relatedness, and exports.

4.2.1 Industrial Design and Exports in the UK

The section on *Industrial Design and Exports in The UK* focuses on the role of the intangible economy in the UK and its impact on sectoral specialisation and productivity. This section begins by highlighting the increasing recognition of the intangible economy in the UK, with significant investments in intangible assets by the private sector. Marrano and Haskel (2006) estimate that the private sector invested approximately £127 billion in intangible assets, accounting for 11% of the country's GDP. The resilience of the UK intangible economy to economic shocks is emphasised, as evidenced by a slight increase in investment in intangible assets in 2020 despite a decline in investment in tangible assets. The section also discusses the bidirectional relationship between individual and regional intangible assets, with individual assets contributing to regional accumulation and the macro environment incentivising firms to hold intangible assets. The importance of intangible assets in promoting sectoral specialisation and productivity is further supported by the findings of Tsakanikas et al. (2022), the role of UK public support in encouraging research and development activities (Haskel and Wallis, 2013). Overall, this section provides an overview of the intangible economy in the UK and sets the stage for the subsequent exploration of the interrelationship between industrial design and exports.

4.2.1.1 Overview of the Intangible Economy in the UK

In the UK, the intangible economy has been recognised as an increasingly significant factor. According to Marrano and Haskel (2006), the private sector in the UK invested approximately £127 billion, accounting for 11% of the country's GDP, in intangible assets. Moreover, compared to tangibles, the UK intangible economy is less impacted by economic shocks. In 2020, investment in intangible assets increased slightly by 0.1% to £134.5 billion, while investment in tangible assets declined by 13.6%.

Using UK firms' financial data as an example, Tahat et al. (2017) argue that intangible assets play a crucial role in long-term growth. At the regional level, the impact of firm-level intangible assets on regional intangible asset accumulation is bidirectional (Kramer et al., 2011). Thus, it can be posited that regional intangible assets are propelled by individual intangible assets, while firms are incentivised to hold intangible assets by the macro environment.

Intangible assets play an important role in promoting both the sectoral specialisation and the productivity in the UK economy. From the UK industry perspective, Tsakanikas et al. (2022) find that the intangible assets can help the sectors to be specialised. Furthermore, it has been evident that the UK public support can encourage R&D and therefore the productivity can be improved (Haskel and Westlake, 2018).

4.2.1.2 Design-driven Economy in The UK

The concept of design economy is first proposed by Heskett (2017) who mentioned that design is not only the tool for product development but also the origin of value added of goods and services by which sustainable growth is promoted. In the UK, creative industries make a significant contribution (Cunningham and Bakhshi, 2008), thereof, design sectors contributed to a large proportion of the gross value added (Design Council, 2016).

The UK design economy has suffered from changes in the past 30 years. According to Q. Sun (2010), at the emerging stage, the UK design is focused on the form and use of new technologies, especially it refers to industrial design; afterwards, design became a broader conceptual framework for activities in a wide range, which suggests the start of design thinking which focuses on solving problems in production, services, and other fields using the ideas of design. Now design can be described as design industries which are suppliers of creative ideas and other design works involved in other traditional sectors, the point of design is meeting people's needs and solving problems in reality (Design Council, 2018). While the importance of design in the UK has been highlighted as the core position in promoting national social and economic development (T. Love, 2007).

4.2.1.3 Design and UK Exports

In addition to the importance of design sectors or design industries, it has been found that design plays a promoting role in innovation (Kembaren et al., 2014), meanwhile, it can also drive the UK exports (Design Council, 2016, 2018). In the UK, the high development level of design leads to: (i) the innovative and high-quality products and services which are attractive in the global market (Crilly et al., 2004); (ii) the goods with a high level of adaptation and differentiation in the foreign market (Afrifa et al., 2018; Larimo and Kontkanen, 2008); (iii) the high level of design capabilities of firms who are able to adjust the market strategy and take the competitive advantage in the global market (Kaleka, 2002).

4.2.2 The Interrelationship of Overseas Design Registration, Overseas Design Relatedness, and Exports: Rationale

The section on *Rationale of Interrelationship of Overseas Design Registration, Overseas Design Relatedness, and Exports* explores the interdependencies among these variables. It highlights the importance of industrial design in protecting intellectual property rights and its potential impact on exports. Overseas design registration can drive exports by providing competitive advantages, improving product innovation, and enhancing reputation. It also motivates firms to register industrial designs overseas. Design relatedness, measured using economic complexity theory, can drive exports by promoting knowledge diversification and innovation. There is a potential interrelationship between overseas design registration and design relatedness. The section is structured as follows: introduction, overseas design registration and exports (including drivers and mutual causality), overseas design relatedness and exports (including drivers and interrelationship), and overseas design registration and design relatedness (including drivers and interrelationship).

4.2.2.1 Overseas Design Registration and Exports

Industrial design is a comprehensive and creative activity involved in mass-produced goods. It aims to optimize the products and production process from multiple aspects, encompassing their form, function, technology, visual and tactile qualities, and user experience (Heskett, 2017). If individuals or firms hope to protect their industrial design and prevent others from copying or imitating the design without permission, the design would be registered as an intellectual property right (IPR) (Thomas, 2011). According to WIPO (2023c), from a legal perspective, a registered industrial design or design patent is recognized as intellectual property and is protected from third-party infringement or imitation.

Industrial design is an important part of patent protection. It can protect the appearance of articles which are not covered by patent. When the patent is protecting a category of products using a specific technology, industrial design focuses on a narrow field of goods with a unique appearance. Therefore, seeking the design protection overseas before exporting facilitates exports and benefits exporters.

Existing research has found that whether or not the intellectual property of products is well protected in destination countries is a determinant of exports (Dong et al., 2022). Moreover, exports are also a motive to seek overseas protection of intellectual property for products (Zhang et al., 2022). Thus, it can be argued that there is probably mutual causality between the overseas patent application and exports. Industrial design, as a kind of intellectual property as well as a kind of patents, seems to also have an interrelationship with exports. This is further discussed in the following subsections.

There is a large body of literature that has found that overseas patent applications can drive exports from the following perspectives: (i) obtaining patent protection in the foreign market helps firms prevent imitation or reproduction of their products, giving them a competitive advantage in the overseas market (C.-H. Yang and Kuo, 2008); (ii) intellectual property protection improves the novelty and innovation of products, leading to high demand in foreign markets and increased exports (Cassiman and Martinez-Ros, 2007; Sweet and Eterovic, 2019); (iii) holding overseas patents helps firms build reputation in foreign countries and increase their visibility in the global market, thereby opening up export channels (Wunsch-Vincent et al., 2015).

Industrial design, also known as design patent, is a specific type of patent that protects the appearance of an article and can also impact export performance. According to Hasanov et al. (2015), patents and industrial designs have been empirically shown to have a positive effect on exports. However, not all types of intellectual property rights (IPRs) drive exports. In the same study, Hasanov et al. (2015) suggest that trademarks do not play such a significant role in exports. The idea that industrial design can drive exports is also supported by other research (Duman, 2021; Gemsera and Leendersb, 2001).

In summary, industrial design drives exports for the following reasons: (i) industrial design makes products attractive, novel, or user-friendly, leading to high demand in foreign markets (Rampino, 2011); (ii) appropriate industrial design allows products to have good adaptability in foreign countries (Calantone, Tamer-Cavusgil et al., 2004), and enables differentiation from similar commodities (Brander and Spencer, 2015); (iii) industrial design in mass production helps reduce costs, allowing for flexible pricing and providing exporting firms with a competitive advantage in foreign markets (Murray et al., 2011).

However, existing research rarely explores the extent to which overseas design registration influences exports. It is often found that the literature does not distinguish whether designs are registered in the domestic market or the foreign market, leading to general perspectives in their conclusions. To fill this gap, this study focuses on cross-border registered designs and explores their impact on exports. Additionally, the reverse relationship between industrial design and exports will also be further discussed.

Unlike the promoting role of industrial design in exports, which is straightforward and widely evident in existing research (J. H. Love and Roper, 2015), the motivating role of exports in design registration is relatively complicated and rarely directly evident in empirical research. Nonetheless, exports are often mentioned in papers as a motivation for firms to apply for patent protection overseas (Milesi et al., 2022; P. J. Smith, 2001). As discussed earlier, industrial design can drive exports, and conversely, exporting to a foreign market also motivates firms to register industrial designs in the destination. Currently, empirical evidence to support the idea that exports also drive industrial design is lacking, but it can be explained in theory.

First, if trade exists between two different countries, exporters would consider industrial design protection in the destination country. This is explained from the perspective of intellectual property protection. In this case, exporters register overseas patents to avoid legal disputes and facilitate business activities. For example, according to Dachs and Pyka (2010), EU countries engage in frequent overseas patenting activities within the EU, driven by their close relationship.

Second, exporters find business opportunities in a foreign market through exporting, thus expanding their knowledge capital in that market. According to findings by Shu and Steinwender (2019), firms engaged in exporting are more motivated to innovate due to potential opportunities in the foreign market.

Third, exporters register designs overseas in order to shift distribution, packaging, or manufacturing activities to a foreign market (WIPO, 2006). When exporters have a long-term intention to trade with a partner country, appropriate arrangements for production and distribution help reduce costs and provide long-term benefits. Direct offshoring involves high sunk costs, so exporting firms usually establish trust with partner countries through exports (Berlingieri et al., 2021).

In summary, overseas industrial design registration is driven by exports for several reasons: (i) Exporters seek legal intellectual property protection for commodities involved in existing exports (Awokuse and Gu, 2015). (ii) Exporters find opportunities in foreign markets through exports and expand their intellectual capital in corresponding markets (Liang and Xue, 2010). (iii) Firms register industrial designs abroad for off-shoring purposes (Canals and Şener, 2014). These reasons are summarized based on theories covered by relevant papers. In addition to this theoretical evidence, this study aims to fill the empirical gap by investigating the extent to which overseas industrial designs are driven by exports.

Reviewing existing research, a clear explanation for the mutual causality of overseas industrial design registration and exports cannot be found. However, this does not mean there is only a one-way relationship between them. As discussed earlier, industrial design, as a design patent and intellectual property right, can be driven by exports. Summarizing the points mentioned in previous paragraphs, the interrelationship between overseas industrial design and exports can be investigated from two broad perspectives: (i) In terms of legal protection of industrial designs, exporting serves as motivation for exporters to register industrial designs abroad (Awokuse and Gu, 2015; Dachs and Pyka, 2010; Milesi et al., 2022; P. J. Smith, 2001). (ii) Exporters seek long-term competitive advantages in foreign markets, and overseas designs are registered to facilitate production or distribution services. Conversely, overseas design patents help exporters maintain a leading position in the market (Calantone, Tamer-Cavusgil et al., 2004; Murray et al., 2011; Rampino, 2011; C.-H. Yang and Kuo, 2008).

4.2.2.2 Overseas Design Relatedness and Exports

Economic complexity theory, proposed by Hidalgo, Klinger et al. (2007), provides a framework to understand the relationship between national productive capabilities and commodity diversity. According to Hidalgo and Hausmann (2009), economies with a high level of economic complexity are able to produce or export a wide range of goods, leading to sustainable economic growth. This theory has also been extended to innovation-related research, known as knowledge complexity (Balland, Boschma et al., 2019; Kogler et al., 2013). The knowledge complexity theory explains regional innovation growth based on existing related knowledge and the sustainable growth of knowledge, which is a key driver of economic growth (Raspe and Van-Oort, 2006).

Currently, knowledge complexity is mainly interpreted as technological complexity and relatedness, measured using patent data (Balland, Boschma et al., 2019; Kogler et al., 2013). Following the methodology used in constructing economic complexity, Kogler et al. (2013) measure technological relatedness using cross-class patent data, capturing how closely related different types of technologies are to each other. Additionally, Balland, Boschma et al. (2019) apply economic complexity methods and use patent data to measure knowledge complexity, emphasizing the importance of the knowledge network, also referred to as the knowledge space in Kogler et al. (2013).

Building upon the methodology proposed in economic complexity theory and its empirical application in knowledge complexity, this study introduces design complexity. Design relatedness, as an application of technology relatedness, is measured using the methodology of economic complexity theory, specifically through cross-class designs. It captures the relatedness between different design classes (Locarno class) by estimating the probability of the quantity of designs registered for two different Locarno classes at the same time. The construction method of this variable will be introduced in the data and methods section.

Overall, current literature suggests that regions with high levels of technological relatedness are more likely to have a comparative advantage in certain industries (Panori et al., 2022; Whittle et al., 2020), leading to increased exports in corresponding regions and industries (He and Zhu, 2018). However, there is a lack of research exploring the reverse relationship between regional knowledge complexity and exports. Nonetheless, theoretical explanations can be discussed from several perspectives.

First, as discussed earlier, exports may have an interrelationship with overseas design registration, including cross-class design registration. Second, in addition to the interrelationship between exports and overseas design quantity, the design quality, measured by design relatedness, is also considered to play a role. Finally, as technological relatedness has been shown to play an important role in exports (He and Zhu, 2018; Panori et al., 2022), design relatedness, as part of knowledge relatedness, is a key driver of economic growth or export growth (Raspe and Van-Oort, 2006). Therefore, it can be speculated that overseas design relatedness and exports may be related to each other.

Just as technology relatedness can drive exports, it is worth investigating whether design relatedness also impacts exports. When focusing specifically on overseas industrial design, since it has been mentioned that exports may affect the quantity of design registrations, it is also worth exploring whether exports can drive the quality of overseas industrial designs. In this research, the quality of design is measured from the perspective of design relatedness.

Knowledge relatedness can drive exports (Jun et al., 2020). In particular, technological relatedness, which is the main measure of knowledge relatedness, has been widely shown to play a promoting role in exports (He and Zhu, 2018; Panori et al., 2022). Industrial design belongs to the wide range of patents, which are intellectual property rights (Brem et al., 2017; P. Lee and Sunder, 2013), and it can be an appropriate measure of knowledge relatedness. Additionally, due to the similarity in data properties between design and patent data (Questel, 2023), the application of methodologies used for patent data to design data is smooth. However, there is no empirical evidence to support the argument that overseas design relatedness can drive exports. Thus, this hypothesis can be proposed based on the theoretical explanation provided below.

First, the impact of design relatedness on exports can be understood from the perspective of regional knowledge relatedness. Design relatedness is measured by cross-sectoral designs, which capture the closeness between two different design categories in a certain region. Therefore, instead of measuring the design quantity of a specific category, design relatedness measures the extent to which a design category can cover cross-class knowledge. The related designs existing in a region can form a knowledge network, and an intensive knowledge network can generate productivity, thereby leading to exports (Howell et al., 2016; Jun et al., 2020).

Second, the impact of overseas design relatedness on exports can be understood from the perspective that design quantity can drive exports. Based on the quantity of cross-class designs, design relatedness is generated, and its nature can be traced back to the number of industrial designs. As discussed earlier, overseas industrial designs may drive exports, and the number of cross-class designs is also considered to play a promoting role in exports. Therefore, it can be argued that design relatedness in the destination market plays a promoting role in exports.

Therefore, it can be argued that design relatedness generated abroad can drive regional export performance. Moreover, similar to the interrelationship between overseas design registration and exports, overseas design relatedness is also considered to be interrelated with regional exports. The reverse relationship between overseas design relatedness and exports will be discussed in the next section.

Existing research has explored the *learning by exporting* theory (Salomon and

Shaver, 2005). It suggests that firms involved in exporting activities are exposed to the global market and new technologies, leading to firm innovation and increased productivity (de Loecker, 2013; Lööf et al., 2015). Using patent data to measure firm innovation outcomes, Aghion et al. (2018) empirically show that exporting benefits firms' patenting activities. Industrial design is an important type of knowledge that firms can learn from exports in new foreign markets, and design relatedness is a measurement of this type of knowledge. Therefore, considering the rationale of *learning by exporting*, it can be speculated that exports can drive design relatedness in the overseas market.

On the other hand, the argument still holds from the perspective of overseas cross-sectoral design registration quantity. As discussed earlier, theoretically, the overseas design quantity can be driven by exports. Therefore, the number of designs registered under more than one Locarno class can also be expected to increase due to exports. In particular, according to research (Balland, Boschma et al., 2019; Kogler et al., 2013) related to technological relatedness, patents that involve different techniques (registered under multiple IPCs) are considered the core of a knowledge space. Similarly, designs that can cover multiple different Locarno classes are regarded as the core that can link different knowledge and serve as the center of the design knowledge network.

Summarising the content above, which has discussed the relationship between overseas design relatedness and exports, the corresponding interrelationship is mainly discussed from the following perspectives: (i) design knowledge drives exports; (ii) the design knowledge is acquired through the learning from exports theory, and it increases along with the increase in overseas design quantity.

4.2.2.3 Overseas Design Registration and Design Relatedness

It has been stated that industrial design is also a form of patent, therefore, design data shares similarities with patent data. Design registration serves as a measure of design quantity, specifically referring to the number of industrial designs registered for protection within a particular territory. Using this measure of design quantity, design relatedness is computed using the methodology of economic complexity theory (Hidalgo and Hausmann, 2009; Hidalgo, Klinger et al., 2007). As a result, it can be reasonably speculated that design relatedness has a direct correlation with design registration.

In comparison to the relationship between overseas industrial design and exports, the relationship between overseas design registration and the generated design relatedness in the overseas market is more straightforward. This can be explored from a measurement perspective, as design relatedness is measured based on design count, it should theoretically have a direct relationship with the frequency of design registration. As illustrated by Kogler et al. (2013), technological relatedness measured using patent data is positively correlated with the number of patents. Therefore, it can be argued that design relatedness, measured using design patent data, is also likely to have a positive correlation with design quantity.

It is reasonable to consider that the number of industrial designs registered in the overseas market is the driving force behind the generated design relatedness in that market, given the computation methods of design relatedness. However, further investigation is warranted because design relatedness is measured in a density form. If the number of cross-class designs is low, the value of design relatedness would also be low, regardless of the large number of designs registered in a specific region. Yet, existing research has not sufficiently explored whether the quantity of knowledge is the driver of knowledge relatedness.

According to Joo and Kim (2010), technological relatedness increases alongside the total number of patents. However, this represents a correlated relationship between the quantity of technologies and technological relatedness. Similarly, Kogler et al. (2013) illustrated a similar increasing trend between technological relatedness and the number of patents, but did not provide an explanation as to the extent to which relatedness is driven or explained by the number of patents. However, the reverse causality between knowledge quantity and relatedness has been extensively discussed in research, which will be addressed in the next section.

Knowledge relatedness is the key driver of knowledge diversification (Breschi et al., 2003; Whittle et al., 2020). Moreover, according to Balland, Boschma et al. (2019), regions with a high level of knowledge relatedness are considered low-risk for the entry of new technologies. Additionally, knowledge diversification, which is driven by technological relatedness, has been shown to play a promoting role in innovation (Garcia-Vega, 2006). Therefore, it can be argued that knowledge relatedness serves as the growth medium for new knowledge.

To the broader concept of knowledge relatedness or the knowledge space (if mapping knowledge relatedness in a region, a knowledge space is generated), technological relatedness is considered as the core empirical measurement (Kogler et al., 2013; Rigby, 2015). Furthermore, technological relatedness is captured using patent data, as patents can be registered across various classes. Moreover, existing research has widely and empirically demonstrated that technological relatedness is the key driver of new technological generation (Balland, Boschma et al., 2019; Ganzaroli et al., 2016; Leten et al., 2016).

As technological relatedness is measured using patent data, similarly, design relatedness is measured using design patent data. The similar data properties of patents and design patents suggest that design relatedness plays a similar role in new knowledge generation as technological relatedness. Therefore, it can be speculated that design relatedness can also drive new knowledge generation in the field of design.

As discussed earlier, new design registration drives design relatedness, while the reverse effect also exists. This suggests the presence of mutual causality between new design registration and design relatedness. Specifically, when focusing on the overseas market, it can be inferred that overseas design registration may have mutual causality with the design relatedness generated in the corresponding foreign markets.

4.2.3 Formulation of the Research Question

The rationale of the interrelationship between design registration, design relatedness, and exports in the overseas market has been sufficiently discussed above. Additionally, the importance of design in the intangible economy of the UK has been highlighted. Hence, the research question can be proposed as follows:

Is there mutual causality existing between UK exports, the quantity of design registered by UK holders in the overseas market, and the corresponding design relatedness generated?

This research question involves three different variables: the quantity of overseas design registration, overseas design relatedness, and exports. Therefore, any combination of two different variables can be investigated to determine whether mutual causality exists. To answer this question, the panel vector autoregression modelling method will be considered. The empirical application of this method will be reviewed in the next section.

4.2.4 Application of PVAR

The Panel Vector Autoregression (PVAR) model is proposed by Holtz-Eakin et al. (1988) as an extension of the Vector Autoregression (VAR) model introduced by Tinbergen (1952). The VAR model is a statistical technique used to analyze the interdependencies among different variables, particularly time series variables within a single observed individual. Building upon the VAR model, the PVAR model serves as a panel counterpart, allowing variables to be composed of multiple individuals, such as different countries, cities, or firms. This enables the application of panel data analysis techniques to the VAR model, which is originally defined for time series data and includes fixed effects. For example, Gabriel and de Santana Ribeiro (2019) utilize the PVAR approach to investigate economic growth and manufacturing with fixed effects.

Some empirical examples demonstrate that PVAR is an appropriate method for investigating the interrelationship between different variables in research related to innovation and economic growth. Ma et al. (2022) evaluated the domestic value-added ratio of exports at the firm level by analyzing patent portfolios and found that optimizing these portfolios could help firms advance in the global value chain. Bottega and Romero (2021) examined how technological competitiveness affects exports and discovered that the patent stock was higher for high-tech goods compared to low-tech ones. Y. Liu et al. (2021) established that patent protection improves product quality, particularly when the initial quality is already high. Spuldaro et al. (2021) used firm-level data to investigate the correlation between innovation and financial performance in emerging markets and found a positive relationship. Wu et al. (2021) explored the role of business groups in the relationship between exports and innovation and suggested that external factors can influence this relationship. Furthermore, Wu et al. (2021) argued that exports can lead to a decline in technological quality.

On the other hand, a large body of literature provides evidence that exports can be enhanced by effective intellectual property rights (IPR) protection in the destination market (Fukui et al., 2013; Kabir and Salim, 2016; Kuźniar and Folfas, 2018). However, these studies also suggest that the motivation for seeking IPR protection in the target market is to avoid imitation or piracy. Therefore, to some extent, exports can be considered as a motivation for registering IPRs in a foreign market. Using PVAR, this study will examine the interactive causality between exports and industrial designs.

Nevertheless, there have been no papers that have analysed the relationship between design and exports using a PVAR (Panel Vector Autoregression) model, which is a useful approach to investigate the potential endogenous relations of variables. Additionally, from an empirical research perspective, although the importance of design has been highlighted, there is still a lack of regional evidence to explore how design drives economic growth. Therefore, by employing the PVAR approach to examine the interdependencies among overseas design registration, design relatedness generated in overseas markets, and the exports of the UK, this study can make empirical contributions from both the application of the PVAR approach and the research on design-driven exports.

4.3 Data and Variables

The section entitled *Data and Variables* provides an introduction to the data used in this study. The dataset consists of three variables: overseas design registration, overseas design relatedness, and export value. The design data is obtained from Questel IP and includes designs registered by owners from 12 regions in the United Kingdom (at the NUTS1 level) and protected in various countries. The export data is collected from UKTRADEINFO and includes information on export value from different UK regions to various countries. The variables are constructed and compiled, and summary statistics are provided for the comprehensive dataset. The dataset comprises 631,372 observations, covering 12 UK regions, 48 countries, 62 commodities, and 28 quarters from 2013 to 2019. The variables are transformed using the inverse hyperbolic function $arsinh(x)$ for further analysis.

4.3.1 Data

The final dataset used for this study involves the construction and compilation of three variables. These variables include the quantity of overseas design registration, which is calculated based on the original design record data obtained from Questel IP. The overseas design relatedness is computed based on the quantity of cross-sector designs registered in the overseas market for a specific period. The export value variable is directly collected from UK Trade Info[2]. The data source is divided into two segments: design data and trade data, each of which is introduced separately. The methodology used to construct the variables is then explained. Finally, a separate subsection presents the summary statistics of the final variables in the comprehensive dataset.

4.3.1.1 Design Data

The design data in this study refers to the flow of design registrations, which is computed using the design records obtained from Questel IP. The data is limited to specific owner countries and protection territories. The design data used in this study covers 12 regions in the UK where the owners are located, as well as a certain number of countries where the design patents are protected. The dataset spans the period from 2013 to 2019 [3], and the computed design count is a quarterly time series. For sectoral analysis, the design count is also calculated based on the Standard International Trade Classification (SITC) commodities.

Therefore, the number of overseas design registrations is specified at the region-country-commodity-quarter level. The region represents the UK location of the owner, the country indicates the location where the design patent is registered for protection,

[2] https://www.uktradeinfo.com/

[3] Taking the interaction of available design data and UK regional trade data, the time is restricted as the period of 2013-2019

the commodity refers to the SITC commodity to which the design patent belongs, and the quarter represents the time frequency for this set of time series.

Figure 4.1 illustrates the UK owner regions covered in the design data, along with the total number of design registrations computed from 2013 to 2019. The data shows that the highest number of design registrations is contributed by overseas design patent owners in London, followed by the South East and South West regions. This suggests that the majority of UK-owned cross-border designs are registered by firms or individuals based in the southern regions. Furthermore, the distribution of overseas design patent ownership decreases from south to north, with Northern Ireland registering the lowest number of overseas designs, as shown in Figure 4.1.

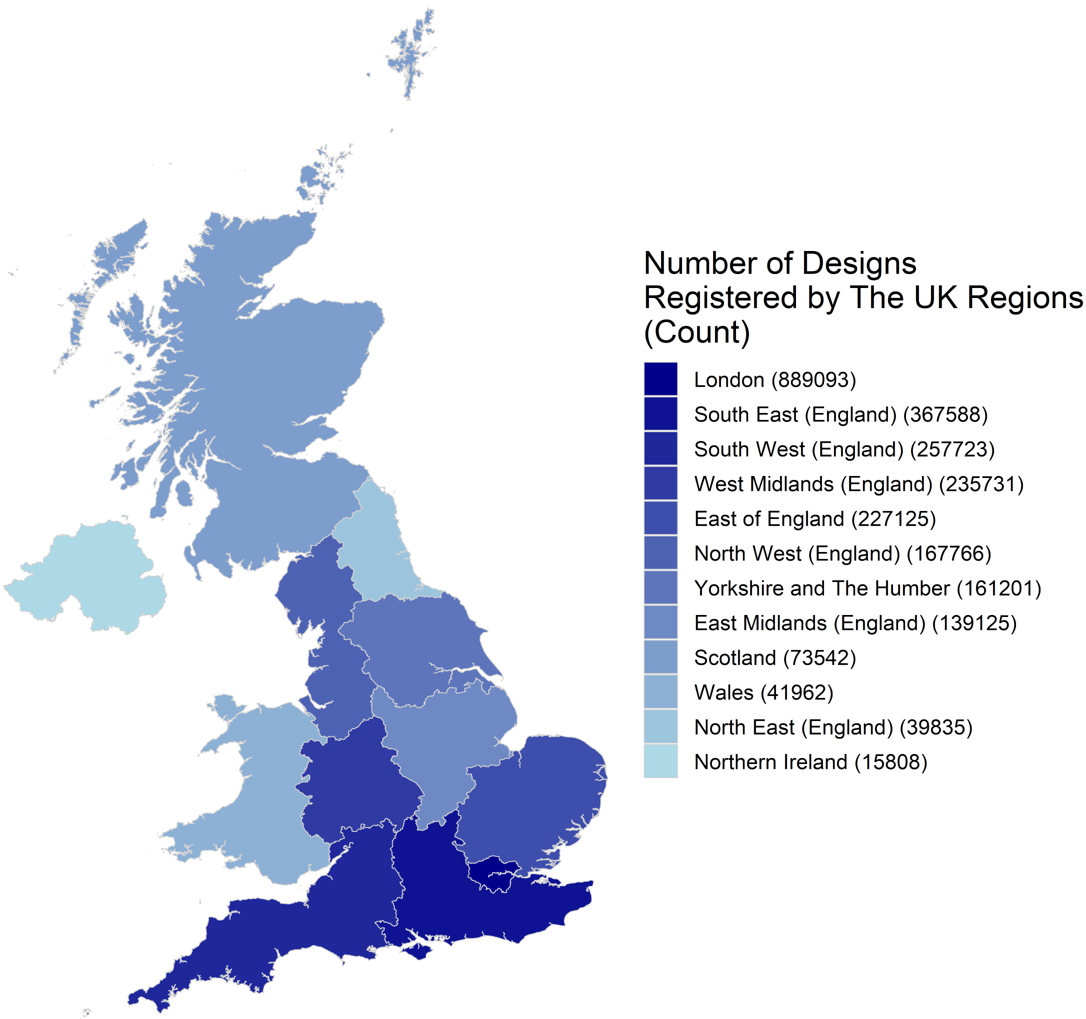


Figure 4.1: Map of UK - Total Number of Oversea Designs Registered by The UK Regions (Cumulative Count in 2013-2019)

Since the design data is a time series, Figure 4.2 illustrates the quarterly temporal change in the number of overseas designs owned by different UK regions. As shown in Figure 4.2, from 2013 to 2019, there is a slight overall decline in the number of UK-owned design patents. Similarly, Figure 4.3 demonstrates a similar declining trend for designs registered in both EU and non-EU countries. Therefore, it can be inferred that UK design patent holders do not show a preference for registering their cross-border designs within or outside the EU.

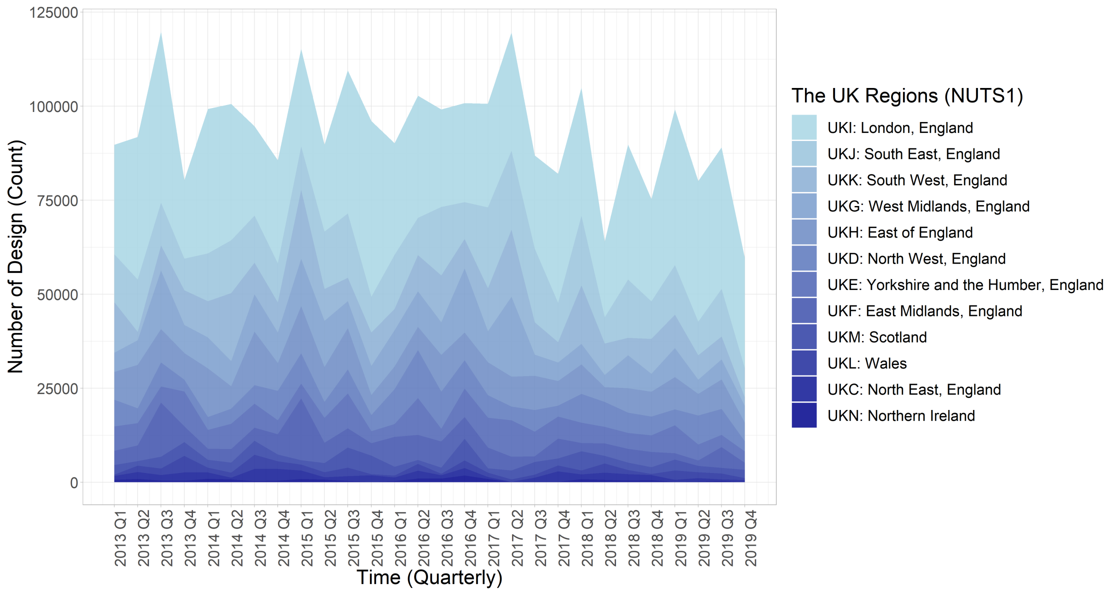


Figure 4.2: Area Chart - Regional Number of Oversear Design Over Time (Quarterly 2013-2019)

Furthermore, the variability in the number of overseas design registrations across different commodities can also be examined. As shown in Figure 4.3, the category of *miscellaneous manufactured articles* has the highest number of designs registered outside the United Kingdom. This can be attributed to the fact that this sector encompasses the manufacturing of various articles, and design patents are used to protect the aesthetics and visual aspects of these articles.

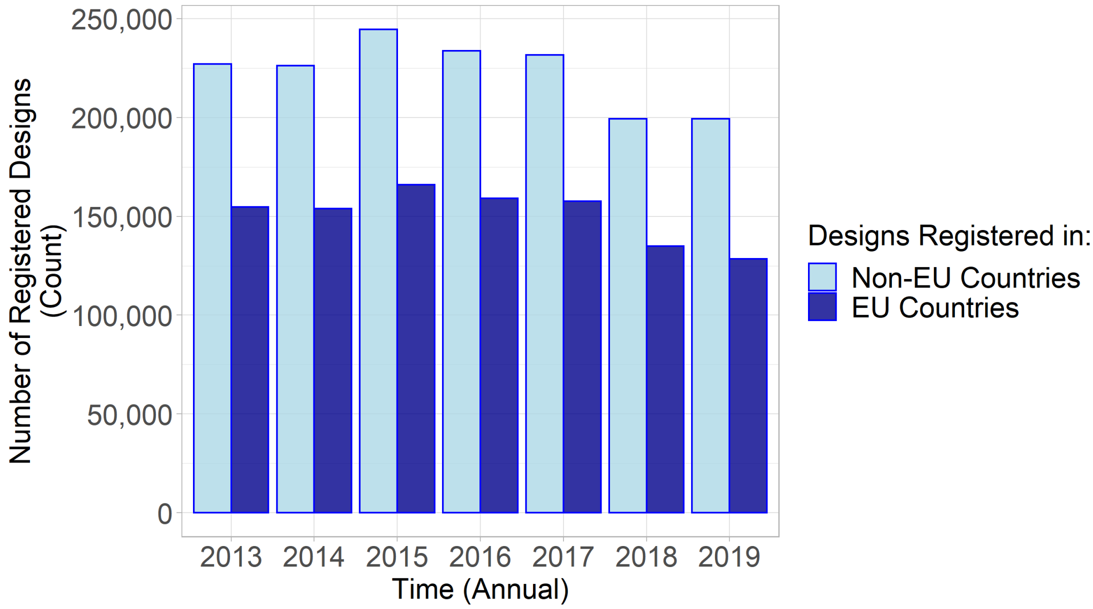


Figure 4.3: Line Chart - Export Value of The UK to the EU or the Non-EU Countries (2013-2019 Quarterly)

Additionally, UK entities operating in foreign markets display a preference for registering designs in the machinery and transport equipment, chemical products, and other manufactured goods categories. Hence, it can be inferred that patenting activities in the realm of industrial design are closely linked to technological advancements, with design patents being registered in sectors characterized by technological intensity. However, applicants tend to prioritize manufacturing sectors due to the intrinsic nature of design patents, which primarily safeguard product appearance closely associated with production processes.

4.3.1.2 Export Data

The export data, collected from UK Trade Info, comprises the UK export value from various UK regions to different countries. This quarterly time series covers the period from 2013 to 2019. Additionally, the export value is reported according to different commodities classified by the Standard International Trade Classification (SITC), providing access to the SITC codes and corresponding export value. In summary, the export data is specified at the region-country-commodity-quarter level. The region represents the UK region where the exporters are located, the country refers to the destination country where the commodities are exported to, the commodity indicates the category of exported goods, and the quarter is the time period during which the exporting activities occur.

The total regional export value of the UK during 2013-2019, as presented in Figure 4.4, reveals that the maximum export value is in the South East region, followed by London and the West Midlands. Unlike the distribution of design ownership, which is concentrated in southern UK, exports are concentrated in the Midlands of the UK. However, similar to the overseas design ownership of the UK, the minimum export value is observed in Northern Ireland.

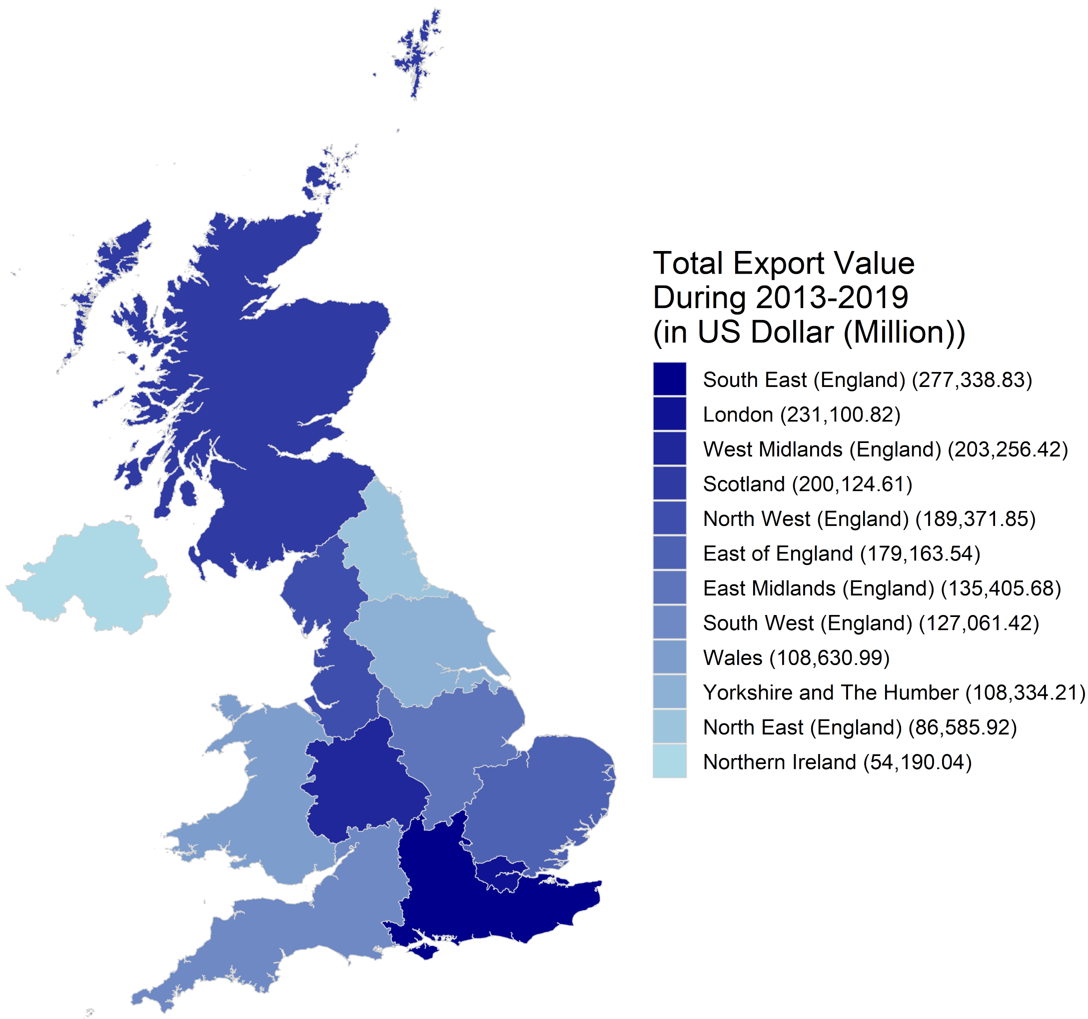


Figure 4.4: Map of UK - Total Export Value by Each Region (Cumulative Value in 2013-2019)

Figure 4.3 illustrates the temporal change in exports to European (EU) and non-European (non-EU) countries, revealing no significant differences. Hence, it can be inferred that UK exporters do not exhibit significant preferences for destinations belonging to the EU or non-EU countries. This contrasts with the registration preferences of UK design holders, as UK design patents are registered more frequently in non-EU countries than in EU countries.

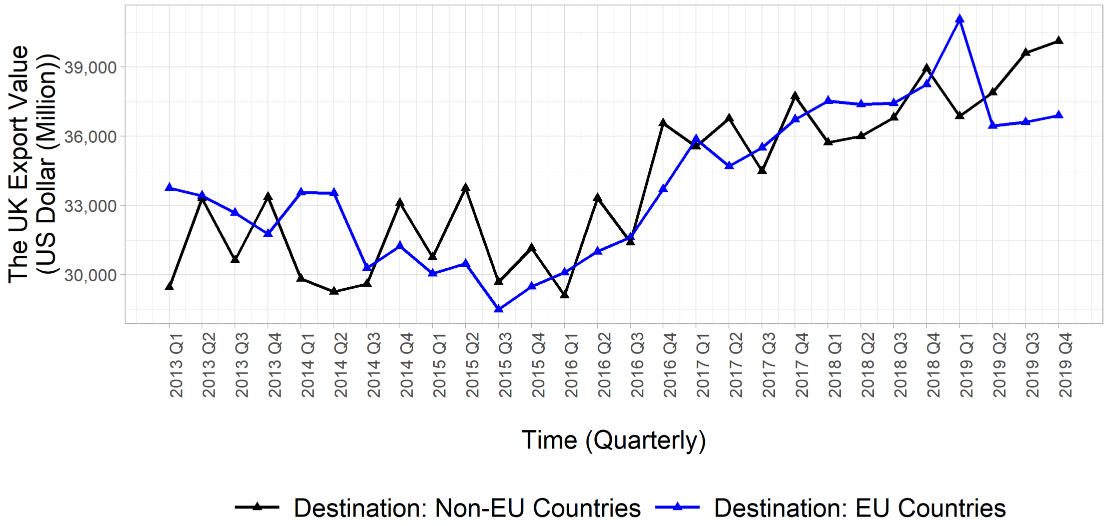


Figure 4.5: Bar Chart - Export Value of The UK to the EU or the Non-EU Countries (2013-2019 Quarterly)

4.3.2 Variables

To address the research question, three variables need to be constructed: the number of overseas design registrations, the overseas design relatedness, and the exports. Utilising the data described in the preceding sections, the variable construction involves both design and export data collected from different sources. The variables are generated separately and then compiled to form the final dataset.

4.3.2.1 Overseas Design Registration

The variable *Overseas Design Registration* represents the number of design patents owned by firms or individuals located in a UK region *i*, registered in quarter *t*, and protected in a non-UK country *j*. Additionally, the number of overseas design registrations is calculated for each commodity *k* coded by 2-digit SITC. Therefore, the variable can be denoted as *Overseas Design Registration*$_{ijk,t}$. The computed values of this variable will be further transformed using the inverse hyperbolic function $arsinh(x)$, so that the transformed values can be applied in further regression analysis.

4.3.2.2 Overseas Design Relatedness

The design relatedness is calculated using the method proposed by Hidalgo, Klinger et al. (2007) in the economic complexity theory, as adopted in the research by Balland, Boschma et al. (2019) to capture the technological relatedness using patent data. Considering the similarity between design patents and traditional patents, this method is reasonably employed in this research. To generate the design relatedness, the number of cross-class overseas designs is computed first. The computation logic is similar to that of the variable *Overseas Design Registration*, with the number of designs owned by the UK region *i*, registered to be protected in country *j* for the commodity *k*, and in the time period *t* being calculated.

However, since it involves designs registered under multiple categories, a co-occurrence matrix of design classes is generated, where the elements represent the number of designs. Using the standardization method by Steijn (2017), the co-occurrence matrix is further standardized, with the elements representing the original relatedness values. These elements can be denoted as $R_{ij,t}^{class_1,class2}$. The total relatedness of a certain design class can be calculated as $TR_{ij,t}^{class_1} = \sum_{class_2} R_{ij,t}^{class_1,class2}$.

Before discussing the variable of overseas design relatedness, another measure needs to be introduced. As the count of overseas design relatedness has been calculated, the design comparative advantage (DCA) can also be computed using the measurement of revealed comparative advantage. The formula for DCA is presented in Equation (4.1), where $N_l^{ij,t}$ represents the number of designs belonging to Locarno class *l*, registered by the UK region *i* to be protected in country *j* in quarter *t*. The variable $DCA_{ij,t}^l$ is a dummy variable that takes the value of 1 if the given region *i* has a comparative advantage for Locarno class *l* in a foreign country *j* at time *t*, and 0 otherwise.

$$DCA_{ij,t}^l = \begin{cases} 1, \text{ if } \frac{N_l^{ij,t} / \sum_l^{N_l^{ij,t}}}{\sum_{ij} N_l^{ij,t} / \sum_{ij} \sum_l N_l^{ij,t}} > 1 \\ 0, \text{ otherwise} \end{cases} \tag{4.1}$$

According to Equation (4.1), DCA is a measure that captures whether a UK region *i* has a comparative advantage in a foreign country *j* for a specific design class *l* at time *t*. When calculating the design relatedness, DCA is included as a factor to eliminate the impact of design capability. For instance, in regions with a high design capability, a large number of designs for a specific commodity may be registered, which is a result of the overall design capability being larger rather than a specialization in that particular commodity. Additionally, to account for the time impact, the sum of total relatedness over time can be used as the denominator. This allows the design relatedness to be generated as a density value. Therefore, the design relatedness can be expressed as:

$$OverseasDesignRelatedness^{l}_{ij,t} = \frac{TR^{l}_{ij,t} \times DCA^{l}_{ij,t}}{\sum_{ij} TR^{l}_{ij,t}} \times 100\% \tag{4.2}$$

Additionally, it should be noted that the process of constructing design relatedness uses the design classification instead of the commodity coded by the SITC. Therefore, the value of design relatedness can be further converted to the SITC code. The conversion table is accessed from the UNCOMTRADE. Finally, after the conversion, the variable can be denoted as *Overseas Design Relatedness*$_{ijk,t}$, with dimensions identical to the variable *Overseas Design Registration*$_{ijk,t}$. The computed values of this variable will be further transformed using the inverse hyperbolic function $arsinh(x)$, so that the transformed values can be applied in further regression analysis.

4.3.2.3 Exports

The variable exports represents the export value of a UK region, denoted as $Exports_{ijk,t}$, to the destination country *j* for the commodity (2-digit SITC) *k* in quarter *t*. This variable is directly generated using the trade data collected from UK Trade Info. Since it has the same dimensions as both the overseas design registration and the overseas design relatedness variables, these three sets of time series can be merged together. Before generating the final dataset to be used in PVAR, all of these three variables need to be transformed using the inverse hyperbolic function $arsinh(x)$. Therefore, the values of each variable used in PVAR are the transformed values.

4.3.3 Summary Statistics of Data

The dataset is merged from the three variables described above, including exports (measured by export value), overseas design registration (measured by number of designs registered in the overseas market), and overseas design relatedness (measured by density of the design knowledge network generated in the overseas market). The final merged dataset contains 631,372 observations, covering 12 UK regions (where exporters and design holders are located in), 48 countries (where goods are exported to and designs are protected in), 62 commodities coded by 2-digit SITC (to which the exported goods and registered designs belong), and 28 quarters from 2013 to 2019.

	Exports	Overseas Design Relatedness	Overseas Design Relatedness
Nbr. Obs.	631372	631372	631372
Min	-0.0000	-0.0000	-0.0000
Max	21.9770	4.9979	4.4585
Median	11.7030	0.0722	0.0002
Mean	10.5374	0.4150	0.0296
Std. Dev.	4.7903	0.7047	0.1084
Number of the UK regions (where exporters and design holders are located in)			12
Number of destination countries (where goods are exported to and designs are protected in)			48
Number of commodities (2-digit SITC codes, to which the exported goods and registered designs belong)			62
Number of quarters			28

Table 4.1: Summary Statistics of Data Employed in PVAR

As presented in Table 4.1, this dataset does not contain missing values. All the variables are transformed using $asinh(x)$, and the summary statistics of both the original variable and the corresponding transformed one are presented here. In the further regression analysis, only the transformed variables will be used.

4.4 Methodology

As it has been discussed in the section of conceptual framework, an interrelationship among overseas design registration, overseas design relatedness, and exports would be examined. In this senario, Panel Vector Autoregression (PVAR) could ofer several advantages. First, PVAR captures the dynamic interactions among variables over time (R. Yang et al., 2023). Second, it is suitable for analyzing panel data, where observations are collected over multiple individuals (cross-section) and time periods (time-series) (Pesaran, 2015). Also, PVAR allows for examining lagged effects of variables on each other, providing insights into the temporal relationships (Grossmann et al., 2014).

Panel Vector Autoregression (PVAR) is widely used by a large body of recent empirical literature (Atsu and Adams, 2021; Burger et al., 2021; Dai et al., 2022; Dogan et al., 2022; Gyedu et al., 2021; H. Liu et al., 2022; Mtar and Belazreg, 2021; Ren et al., 2021; Su and Li, 2021; Yuan et al., 2022) to estimate the dynamic relationship between variables where potential interactive causality would exist. Due to panel VARs being demonstrated as an appropriate tool to estimate the dynamic interdependencies and changing pattern of variables (Canova and Ciccarelli, 2013), this study will employ the PVAR model to investigate the interactive relationship among design registration, design relatedness, and export value.

Referring to the model specification of PVAR proposed by Holtz-Eakin et al. (1988), I. Love and Zicchino (2006) examined the panel VAR model and estimated it using the General Method of Moments (GMM) estimator. Additionally, this study will use the Stata package developed by Abrigo and Love (2016) and I. Love and Zicchino (2006) for the estimation work. Following the system structure of the model specification used by Ahlfeldt et al. (2015), the underlying theory to specify the PVAR model is based on Holtz-Eakin et al. (1988) and I. Love and Zicchino (2006). PVAR is described as Equation (4.3).

$$y_{ijk,t} = A_0 a_{ijk,t} + \sum_{l=1}^{p} M_l y_{ijk,t-l} + \theta_{ijk} + \delta_t + \epsilon_{IkujiroNonaka,t} \tag{4.3}$$

Where $ijk \in \{1, 2, 3, \ldots, N\}$ is regarded as a complete subscript denoting the individuals in the panel data, and $t \in \{1, 2, 3, \ldots, T\}$ is the time index, the lag order l is determined using information criteria. After model selection, the lag order is denoted as p, which represents the highest order of the sum of variables $y_{ijk,t}$. The PVAR model with a lag order of p is abbreviated as PVAR(p).

In the context of this study, i represents the UK region at the NUTS1 level, j denotes the destination country where the UK regions register designs or export commodities to, and t indicates the time index of the panel model. The dependent variable in the panel data, denoted as $y_{ijk,t}$, is an $n \times 1$ vector, while $y_{ijk,t-l}$ represents the lagged $y_{ijk,t}$ with a lag order of 1. The associated parameter matrices $M_1, \ldots, M_l$ are $n \times n$ and time-invariant. To account for possible dummies or seasonal changes (Canova and Ciccarelli, 2013), the vector $a_{ijk,t}$ is an $n \times 1$ vector of determinants that includes potential trends or a constant. This vector is associated with an $n \times n$ parameter matrix A_0. The unobserved individual-specific variables are captured by fixed effects θ_{ijk}, while fixed effects δ_t account for time-specific unobserved variables. The error term is denoted as $\epsilon_{ijk,t}$.

4.4.1 Model Specification

Before delving into the model specification of PVAR, it is crucial to note that this study aims to explore the interrelationship among overseas design registration, overseas design relatedness, and exports. Consequently, only three variables, each measuring these aspects, will be employed. These measures have been thoroughly discussed in the section on data and measures.

Limiting the number of variables in PVAR analysis, as advocated by Abrigo and Love (2016), offers several advantages. With fewer variables, the model becomes simpler and more interpretable, enhancing accessibility for analysis. This reduction in variables decreases the model's complexity, potentially improving estimation results and yielding more robust findings. By focusing on a select number of variables, researchers can delve deeper into the relationships of interest without being hindered by extraneous factors. Additionally, a smaller set of variables enhances computational efficiency, reducing the burden of regression analysis and expediting the analytical process.

To provide more specificity, the PVAR model is specified as Equation (4.4). The variables employed by PVAR are defined in the context of this study, while the component $A_0 a_{ijk,t}$ is excluded from this model as the fixed effects can adequately capture the potential unobserved variables initially included in $A_0 a_{ijk,t}$.

The vector $\begin{pmatrix} NbrDes_{ijk,t} \\ RelDensDes_{ijk,t} \\ Exp_{ijk,t} \end{pmatrix}$ represents the dependent variables. $NbrDes_{ijk,t}$ denotes the number of designs owned by a UK region i, registered in quarter t for protection in country j with respect to commodity k. $RelDensDes_{ijk,t}$ corresponds to the design-relatedness density. $Exp_{ijk,t}$ represents the export value, where i is the source region, j is the destination country, k is the exported commodity, and t denotes the quarter when the export occurred.

$$\begin{pmatrix} RelDensDes_{ijk,t} \\ NbrDes_{ijk,t} \\ Exp_{ijk,t} \end{pmatrix} = \sum_{l=1}^{p} \left(M_l \times \begin{pmatrix} RelDensDes_{ijk,t-l} \\ NbrDes_{ijk,t-l} \\ Exp_{ijk,t-l} \end{pmatrix} \right) + \delta_t + \epsilon_{ijk,t} \quad (4.4)$$

In order to incorporate δ_t as a time fixed effect in the model, it is necessary to apply a Helmert transformation to the data (Holtz-Eakin et al. (1988)). This transformation removes the fixed effects. Subsequently, the model uses the untransformed variables as instruments for the Helmert-transformed variables.

4.4.2 Model Selection

To select a lag order for PVAR, Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC), and Hannan-Quinn information criterion (HQ) should be computed to determine the lag order that produces the minimum value of the information criteria. In this section, these three information criteria will be introduced and compared with each other. When three different criteria suggest distinct lag orders, their results must be evaluated as a whole, considering both the sample size and model complexity; this will be discussed in more detail in the Results section.

AIC is a measure that can be used to compare and select the best model out of a list of candidate models for a given dataset. The AIC value is calculated as a function of the likelihood of the data given the model and the complexity of the model (see Equation (4.5)). Lower values indicate a better fit between the model and the data.

$$AIC = -2ln(MaxLogLikelihood) + 2 \times Nbr.Parameters \tag{4.5}$$

Bayesian Information Criterion (BIC) is a criterion used for model selection among a set of models; it is based on the trade-off between the goodness of fit of the model and the complexity of the model. BIC penalises complex models (i.e., with more parameters) that provide only a small improvement in fit compared to simpler models, by assigning them a higher BIC score. The goal of using BIC is to identify the most parsimonious model that explains the data.

$$BIC = -2ln(MaxLogLikelihood) + Nbr.Parameters \times ln(Nbr.Obs) \tag{4.6}$$

Likewise, the Hannan–Quinn information criterion (HQC) is also a method used to compare and select the best model from a set of candidate models, similar to AIC and BIC. It is based on Akaike's Information Criterion (AIC) and Bayesian Information

Criterion (BIC), but applies different penalties for higher-order parameters. The HQC penalises the complexity of the model more strongly than either the AIC or BIC, making it useful for choosing the most parsimonious model from a set of candidates with similar fit characteristics.

$$HQ = -2ln(MaxLogLikelihood) + Nbr.Parameters \times ln(ln(Nbr.Obs)) \quad (4.7)$$

Comparing three types of information criteria, it is evident that AIC selects a model based on the number of parameters and maximum likelihood. Additionally, BIC and HQ include the number of observations in their calculation; they are similar to each other (Claeskens and Hjort, 2008). As BIC is known for selecting a *true model*, AIC allows for uncertainty in reality by accepting probabilities lower than one (Burnham and Anderson, 1998). Furthermore, HQ is akin to BIC but assigns varying weights to different levels of complexity, imposing heavier penalties on larger models than simpler ones.

In this study, three different information criteria were calculated to select the model and discussed further in the results section. These criteria were determined by the maximum log-likelihood; however, the log-likelihood was taken as a negative value and then included in the calculation formula. Therefore, the model with the lowest value of the information criteria was selected.

4.4.3 Parameter Estimation

Parameter estimation in panel VAR is the process of estimating the coefficients of the model variables given a panel of data. Once the lag order of the model is selected, the goal of parameter estimation is to find the best set of parameters that explain the relationship between the variables and the observed outcomes in the data. This involves using maximum likelihood optimization algorithms to identify the optimal parameter values given the data.

The Hansen-J test cannot be applied, as this model employs untransformed variables as instruments for Helmert-transformed variables in the model. Therefore, the number of instruments is equal to the number of endogenous variables [4].

4.4.4 IRF Analysis

The impulse response function (IRF) is a mathematical representation of the output of a dynamic system when presented with a brief input signal (shocks), called an impulse. An impulse is considered to be a very short-duration signal, with amplitude and duration tending towards zero. The impulse response of a system provides a complete description

[4]The estimation will be conducted using STATA package $pvar2$. This package is using the PVAR model proposed by I. Love and Zicchino (2006), the STATA command is developed based on the package $pvar$ by I. Love and Zicchino (2006), and is widely used by existing research (Chang and Zhang, 2015; Li et al., 2022; Ouyang and Li, 2018; F. Wang et al., 2021; Y. Wang et al., 2021) in different areas.

of the output of the system for any arbitrary input. It characterises the dynamic response of the system with respect to changes in the inputs.

The analysis of Panel VAR would be conducted according to the Impulse Response Function (IRF), and the confidence interval of 95% of the response with respect to shocks would also be calculated and used to determine the statistical significance. Corresponding impulse responses and confidence intervals are computed based on 1,000 Monte Carlo simulations.

The IRF results are analysed in the ribbon-line chart. The y-axis represents the impulse response, while the x-axis denotes the time; thus, the impulse response across time is plotted as a line. Additionally, the 95% confidence interval can be plotted as the shadow area (error band), which indicates the significance level. In other words, an IRF plot consists of the response of a variable to one unit standard deviation of another variable over a period of time. The unit of the y-axis is expressed in units of standard deviation, and the unit of the x-axis is specified in quarters.

4.4.5 Granger Causality

To gain a better understanding of the interactions between variables, researchers often employ Granger Causality Tests. Model selection using information criteria can determine the 'best' model based on current variables and multiple lag orders; however, this technique does not provide insight into the extent of causality between the variables. In contrast, Granger Causality Tests examine temporal precedence and assess the strength of causal relationships. This statistical tool is based on the assumption that if the lagged values of one variable can predict another variable, then there is likely a causal connection between them. Granger causality tests are commonly used in panel vector autoregression (VAR) models to determine if past values of one variable explain present values of the other.

The null hypothesis of a Granger Causality Test states that there is no causal relationship between the two variables, while the alternative hypothesis suggests that one variable significantly influences the other. The Wald test, a statistical test used to assess the significance of coefficients in a regression model, is employed in the context of Granger causality. Specifically, the Wald test examines the significance of the lagged values of the potential causal variable in predicting the dependent variable. By comparing the F-statistic obtained from the Wald test to critical values, researchers can determine whether there is evidence of Granger causality between the variables. The aim of Granger causality Wald tests is to provide empirical evidence regarding the direction and significance of causal relationships between time series variables. In this study, these variables include design relatedness, design registration, and export.

4.4.6 Forecast-error Variance Decompositions (FEVD)

Forecast-Error Variance Decompositions (FEVD) in panel VAR are a method for decomposing the total forecast error variance into the contributions of individual variables (Lütkepohl, 2005). It provides a percentage value that indicates the effect of exogenous shocks from other variables on a given variable. The Impulse Response Function (IRF) captures the absolute variation of response to a shock over time, while FEVD can show the relative influence of variables. Moreover, FEVD can be used to determine whether differences in forecasts between different time periods are due to structural changes or simply variations in the impact of individual shocks.

4.5 Results

The results will be presented in accordance with the sequence of the methodology section. (i) Model selection, based on the previously confirmed model specification, will be performed to select a lag order for the Panel VAR model; the corresponding results will be presented in this section. (ii) Once the lag order has been confirmed, parameter estimation will be done, and the estimated coefficient results will be shown in the parameter estimation section; however, the results will be analyzed through the Impulse Response Function instead of the coefficients. (iii) The impact of each variable on another one, along with its statistical significance, will be presented and discussed further in the IRF analysis section. (iv) Since the IRF does not determine the causal relationship between variables, the Granger Causality Test will be utilized to investigate their causality, as depicted in the Granger Causality section. (v) After discussing the impulse response and causality, the analysis will focus on the influence share of the other two variables on a particular variable, which will be outlined in the FEVD section.

4.5.1 Model Selection

As discussed in the methodology, three different information criteria (AIC, BIC, and HQ) have been utilised to select the lag order of the Panel VAR model. As can be seen in Table 4.2, these information criteria do not all point to the same lag order. Therefore, a comparison of their respective pros and cons must be conducted to select a lag order that aligns more closely with the model used in this study.

Lag	AIC	BIC	HQIC
1	1.6666	2.9685*	2.0327
2	1.6445	2.9939	2.0246
3	1.6277*	3.0284	2.0229*
4	1.6526	3.1089	2.0642
5	1.6742	3.1909	2.1037
6	1.6862	3.2686	2.1352

Table 4.2: Model Selection: Information Criteria

Table 4.2 indicates that AIC and HQ have both chosen a lag order of 3. Conversely, BIC suggests a lag order of 1. This discrepancy can be attributed to the substantial sample size of the regression (541,176 observations), as BIC is more appropriate for smaller samples. Consequently, the utility of BIC in model selection for this study is limited. In contrast, both AIC and HQ concur on the selection of a lag order of

3. As previously mentioned, AIC is capable of accommodating uncertainty in real-world scenarios, while HQ considers both sample size and model complexity. When these two information criteria yield the same lag order recommendation, it provides a stronger basis for model selection. Given that the different information criteria propose lag orders of both 1 and 3, this study will examine all lag orders ranging from 1 to 3 for the PVAR. This approach allows for a comparison of regression results across different lag orders and facilitates further analysis.

4.5.2 Analysis on PVAR(1)

The results of the PVAR(1) model for the relationships between overseas design registration, overseas design relatedness, and exports will be analysed in this section. Valuable insights into the dynamic interactions and causalities among these variables in the international design landscape are provided by the PVAR(1) model. The statistical significance and reliable regression coefficients are demonstrated in the parameter estimation results. The response of each variable to shocks from the other variables will be examined through the analysis of the impulse response functions (IRFs). The immediate and lagged effects of shocks on each variable can be understood through the IRFs. Causal relationships between the variables will be examined using Granger Causality Wald Tests. Additionally, the contributions of each variable to the variation in the others will be analysed through a forecast-error variance decomposition (FEVD). This section aims to shed light on the international design landscape by providing a comprehensive understanding of the relationships and dynamics among overseas design registration, overseas design relatedness, and exports.

4.5.2.1 Parameter Estimation of PVAR(1)

The parameter estimation for the PVAR(1) model, estimated using the GMM estimator, is presented in Table 4.3. The instrumental variables used in this estimation are the untransformed values of each variable. With a lag order of 1, this model incorporates 9 instrumental variables, with three instruments for each dependent variable. The analysis of the results is beyond the scope of this section, as the discussion of impulse response needs to consider the memory in the process, which is illustrated through IRF plots.

Group variable: ijk			Number of groups = 22549
Number of obs = 586274			Number of equations = 3
Number of instruments used: 9			AIC = 1.66657; BIC = 2.96846; HQIC = 2.03271
	Design Relatedness Density	Nbr. Design	Exports
Lag1. Design Relatedness Density	0.0585***	0.0017	0.0418**
	(0.0061)	(0.0091)	(0.0157)
Lag1. NbrDes	0.0389***	0.2800***	0.0348**
	(0.0026)	(0.0061)	(0.0107)
Lag1. Exports	0.0010*	0.0166***	0.3951***
	(0.0004)	(0.0013)	(0.0052)
Instruments used:	Lag1 of Design Relatedness Density; Lag1 of Nbr. Design; Lag1 of Exports		
Hansen Test for over-identification:	Just identified - Hansen statistic is not calculated		
Note: Time effects have be demeaned, and All equations use the same set of Instruments. The model uses untransformed variables as instruments for the helmert-transformed variables in the model			

Table 4.3: Regression Results - PVAR(1)

4.5.2.2 IRF Results of PVAR(1)

The impulse response of the PVAR(1) model is depicted in Figure 4.6. It is evident that selecting a lag order of 1 yields statistically significant regression results, as indicated by the narrow error bands in each subgraph. Additionally, all the results demonstrate positive and significant effects, indicating that each of the three variables positively responds to shocks from the other two variables. The response of each dependent variable to shocks from other variables will be discussed individually in the subsequent subsections of this section.

4.5.2.2.1 IRF Results of PVAR(1): Response of Design Relatedness to Shock of Design Registration

When considering the response of overseas design relatedness to shocks from other variables, it is important to note that the most significant and largest effect is observed from its own past values. This can be observed from the y-axis value range, where the impulse response of design relatedness to itself ranges from [0, 0.08), while the impulse response of design relatedness to the shock of design registration ranges from [0, 0.01). This suggests that overseas design relatedness is influenced by both the existing design relatedness that has been established in overseas markets and the existing design registrations in those markets. In comparison, the effect resulting from shocks in past design registrations is not as substantial as the impact of past design relatedness generated in overseas markets.

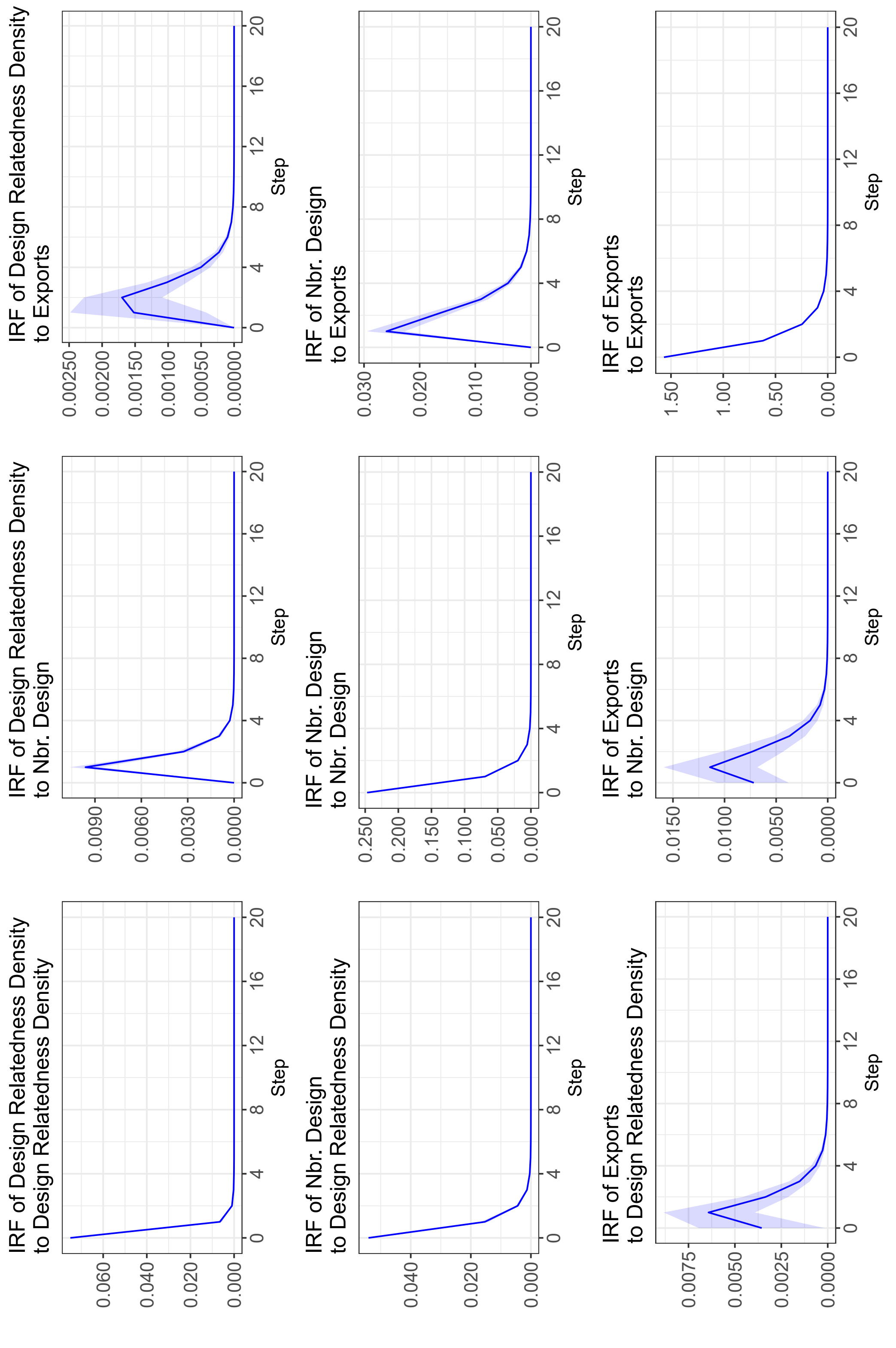


Figure 4.6: Impulse Response - PVAR(1)

4.5.2.2.2 IRF Results of PVAR(1): Response of Design Relatedness to Shock of Exports

Furthermore, the significance of the response of design relatedness to the shock of exports is not as pronounced as its response to the shock of design registrations in overseas markets. This observation is apparent from the y-axis value ranges of the impulse responses of design relatedness to its own past values, the shock of design registrations, and the shock of exports. Additionally, when comparing the impulse response of design relatedness to the shock of design registrations in overseas markets with the impulse response to exports, it becomes evident that the error band for the 95% confidence interval is wider for the shock of exports, while it is narrower for the shock of design registrations in overseas markets. Based on this observation, it can be concluded that design relatedness exhibits a more significant response to the shock of design registrations in overseas markets compared to the shock of exports. However, to thoroughly analyze the extent to which variables can affect each other, a variance decomposition will be conducted. Therefore, a definitive conclusion can only be drawn once the variance decomposition is completed.

4.5.2.2.3 IRF Results of PVAR(1): Response of Design Registration to Shock of Design Relatedness

The response of design registrations to shocks from various variables, including itself, is presented in the second row of Figure 4.6. One notable observation is that the response of design registrations to design relatedness begins in the initial period when the shock is released, referred to as period 0 in this study. This implies that design registrations in overseas markets exhibit an immediate response to shocks in design relatedness generated in those markets. In contrast, the response of design relatedness to design registrations in overseas markets is lagged by one order, occurring after the shock of design registrations is initiated. However, it is important to note that the most statistically significant and large effect is observed from the past values of the design registration variable, as evident from the value ranges of the y-axis.

4.5.2.2.4 IRF Results of PVAR(1): Response of Design Registration to Exports

Furthermore, it is evident that the variable design registration exhibits a positive response to the shock of exports. However, although this effect is statistically significant in the case of PVAR(1), it is not as substantial as the impact of design relatedness on design registration in overseas markets. This observation is derived from the IRF analysis. Conversely, in contrast to the absence of delays in the impulse response of design registration to the shocks of design relatedness and itself, design registrations tend to respond to the shock of exports with a lag of one period after the shock is initiated. To arrive at a definitive conclusion, a variance decomposition of design registration is necessary. Hence, this section can only provide an analysis from the perspective of IRF, and the conclusion must take into consideration the FEVD.

4.5.2.2.5 IRF Results of PVAR(1): Exports to Design Relatedness

The impulse response of exports to design relatedness in all three variables, including design relatedness, design registration, and exports itself, initiates from the initial period, denoted as period zero. This indicates that exports tend to promptly respond to design shocks from both the perspectives of quantity and relatedness. Therefore, in comparison to the design response to the shock of exports, exports are more likely to be influenced by design factors first.

Similarly, analogous to the response of design variables to different shocks, exports exhibit the largest response to itself. This suggests that other variables, such as overseas design registration and overseas design relatedness, do not play as significant a role as existing exports in promoting regional exports. Specifically, according to the IRF plots, the effects of design registration on exports tend to be larger than the effects of design relatedness. This observation can be further analyzed through the FEVD.

4.5.2.2.6 IRF Results of PVAR(1): Exports to Design Registration

The variable export exhibits a positive response to the shock of overseas design registration from the period when the shock is initiated. Furthermore, this response is statistically significant, indicating that exports tend to increase due to existing design registrations in the overseas market. This effect can last for six quarters, which corresponds to the memory in the process. In comparison to the response of design registrations to the shock of exports, it is evident that exports respond to design registration more rapidly than design registration responds to exports. However, the impact of exports on design registration tends to persist for a longer duration than the impact of design registration on exports.

4.5.2.3 Granger Causality of PVAR(1)

The results of the parameter estimation display the regression outcomes, while the IRF plots demonstrate the extent to which three distinct variables are influenced by each other. However, the impulse response alone cannot serve as evidence for the potential causality issues within the variables of overseas design registration, overseas design relatedness, and exports. Therefore, the examination of causality is conducted through Granger Causality Wald Tests. Table 4.4 presents the results of the Granger causality test for PVAR(1).

Dependent Variable	Excluded	Chi-square	Degree of Freedom	p-Value
Design Relatedness Density	Nbr. Design	226	1	0.0000
Design Relatedness Density	Exports	6	1	0.0161
Design Relatedness Density	All	432	2	0.0000
Nbr. Design	Design Relatedness Density	0	1	0.8490
Nbr. Design	Exports	156	1	0.0000
Nbr. Design	All	158	2	0.0000
Exports	Design Relatedness Density	7	1	0.0076
Exports	Nbr. Design	11	1	0.0011
Exports	All	17	2	0.0002

Table 4.4: Granger Causality Wald Tests - PVAR(1)

The null hypothesis posits that the variables in the second column of Table 4.4 are not Granger-causal for the variables in the first column. This implies that the estimated coefficients of the first-order-lagged variables in the second column are significantly zero. Rejecting the null hypothesis indicates that the variables in the second column do Granger-cause the variables in the first column. With a significance level of 0.05, it is evident that the variable design relatedness does not Granger-cause design registration. However, Granger causality can be identified between other pairs of variables. Granger causality serves as an additional analysis to the IRF examination and can be further discussed in light of the Forecast-error Variance Decompositions.

4.5.2.4 Forecast-error Variance Decompositions (FEVD) of PVAR(1)

The Forecast-error Variance Decomposition (FEVD) of PVAR(1) is divided into three groups, with a separate analysis conducted for each dependent variable. The first step involves generating a comprehensive overview of the variance decomposition for each variable, including its own impact, to assess the extent to which the variable is influenced by itself and other variables. Subsequently, the analysis excludes the self-impact and focuses on illustrating the impacts from the other two variables.

4.5.2.4.1 Forecast-error Variance Decompositions (FEVD) of PVAR(1): Design Registration

The variation in design registration in overseas markets is predominantly influenced by the inherent shocks of the design itself, as illustrated in Figure 4.7. The contribution of both design relatedness and exports to this variation is approximately 10%. However, in comparison to exports, design relatedness exhibits a greater tendency to contribute to the variance of design registration.

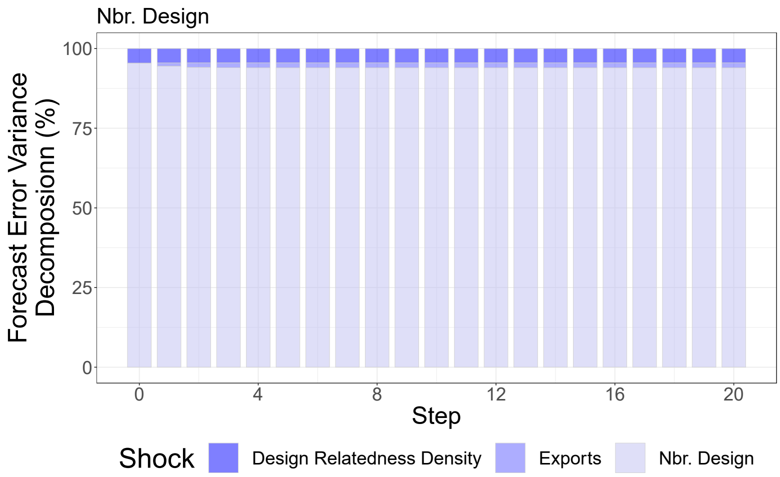


Figure 4.7: Forecast-error Variance Decompositions (FEVD) of Design Registration - PVAR(1)

Furthermore, the impact of export shocks on the variance of design registration initiates from period 1, as opposed to period 0, aligning with the previous observations in IRF plots. Conversely, the shock of design relatedness tends to influence the variance of design registration from period zero upon its initiation. To assess the contribution of design relatedness and export shocks to the variation in design registration, Figure 4.8 presents the decomposition of design registration excluding the contribution of self-shocks. The analysis reveals that the effect of design relatedness surpasses that of exports on design registration.

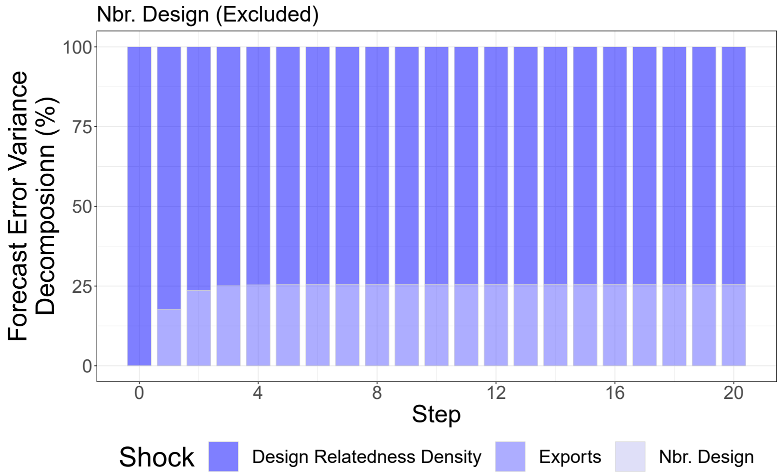


Figure 4.8: Forecast-error Variance Decompositions (FEVD) of Design Registration (Self-exclusion) - PVAR(1)

However, despite the notable influence of design relatedness on design registration as indicated by the FEVD analysis and considering the Granger Causality Tests of PVAR(1), it should be noted that design relatedness does not Granger-cause design registration. It can be argued that exports are the sole contributors to the variation in design registration, excluding the design registration variable itself.

4.5.2.4.2 Forecast-error Variance Decompositions (FEVD) of PVAR(1): Exports

Regarding the impact of shocks on the variance of exports, Figure 4.9 reveals that the export variable is primarily influenced by its own shock rather than the other two variables. The graph indicates that nearly 100% of the variance is attributed to the self-shock. However, based on the Granger causality test, both design registration and design relatedness are considered to Granger-cause exports. Hence, the contribution of shocks from design registration and design relatedness to the variance of exports cannot be disregarded, despite their relatively low magnitude.

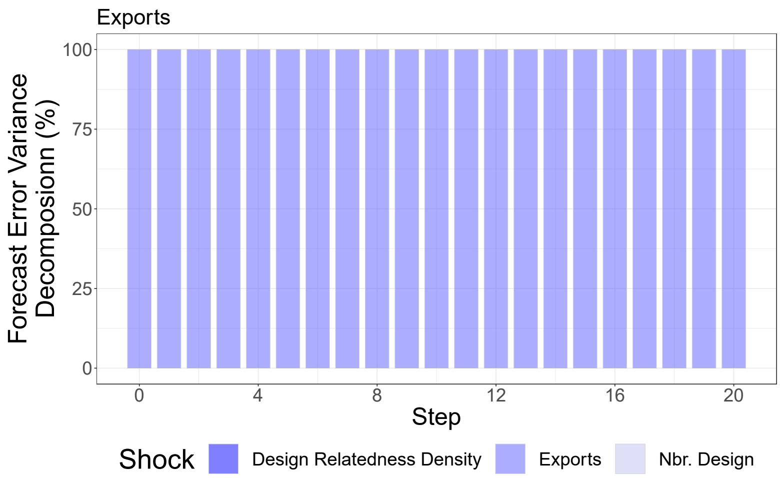


Figure 4.9: Forecast-error Variance Decompositions (FEVD) of Exports - PVAR(1)

Hence, a decomposition of the variance of exports is performed by considering only the shocks of the other two variables, namely design registration and design relatedness. The resulting decomposition is depicted in Figure 4.10. It is evident that the shocks of design relatedness and design registration make non-zero contributions to the variation of exports. Moreover, this figure provides a clear distinction in the contributions between design registration and design relatedness.

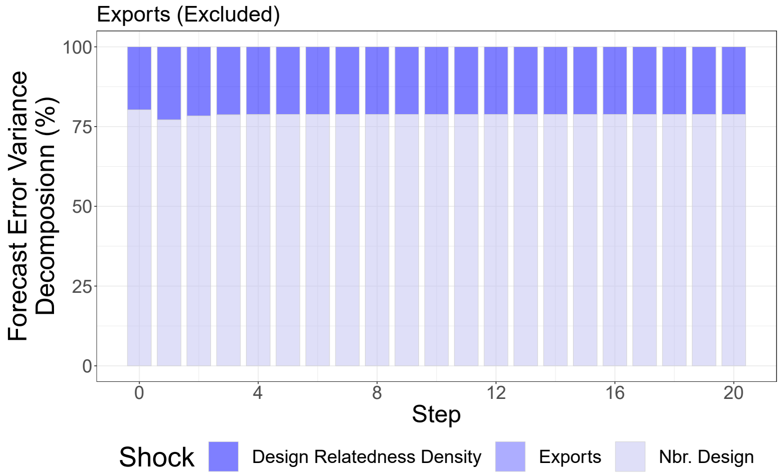


Figure 4.10: Forecast-error Variance Decompositions (FEVD) of Exports (Self-exclusion) - PVAR(1)

The variation of exports is influenced by the shocks of design relatedness and design registration, which commence from period zero, consistent with the IRF analysis of PVAR(1). Furthermore, it is apparent that design registration exerts a greater impact on the variation of exports compared to design relatedness. The Granger Causality Tests confirm that both design relatedness and design registration Granger-cause exports, indicating their contribution to the variation of exports. However, the effect of design registration is more pronounced than that of design relatedness.

4.5.2.4.3 Forecast-error Variance Decompositions (FEVD) of PVAR(1): Design Relatedness

The Figure 4.11 presents the FEVD of design relatedness, indicating that the variance of design relatedness is primarily influenced by its own shocks according to PVAR(1).

The second most significant effect on the variation of design relatedness is attributed to the shock of design registration. However, the contribution of the shock of exports on the variation of design relatedness is not clearly evident from Figure 4.11. To gain a clearer understanding, it is necessary to plot the contribution of shocks from design registration and exports on the variation of design relatedness separately, excluding the impact of design relatedness itself. This will allow for a more explicit illustration of the contributions from the other two variables.

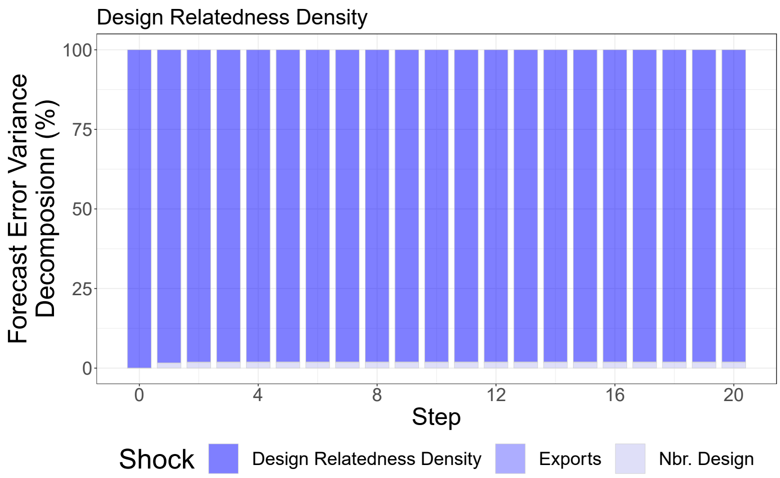


Figure 4.11: Forecast-error Variance Decompositions (FEVD) of Design Relatednes - PVAR(1)

The contribution of shocks from design registration and exports to the variation of design relatedness is depicted in Figure 4.12. It is evident that, in comparison to the contribution of exports, design relatedness is more significantly influenced by design registration. The impact of exports on the variation of design relatedness is relatively small. However, it is worth noting that the contribution of the shock of exports exhibits an increasing trend over time.

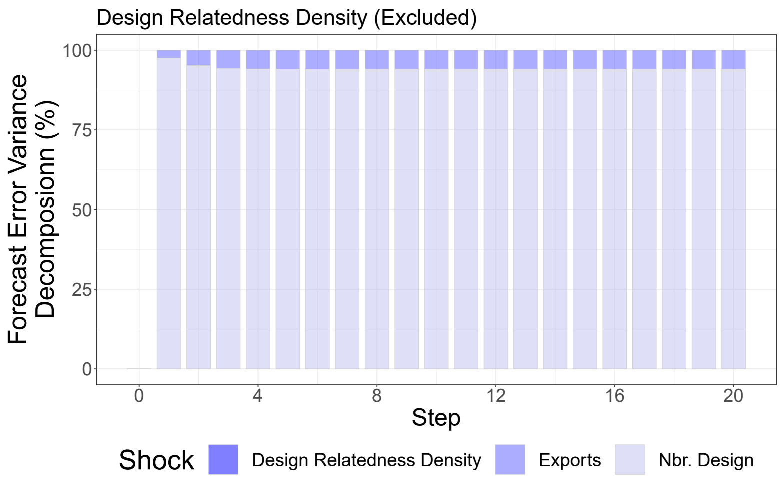


Figure 4.12: Forecast-error Variance Decompositions (FEVD) of Design Relatedness (Self-exclusion) - PVAR(1)

Based on the Granger Causality Tests, it can be concluded that both design registration and exports Granger-cause the variation in design relatedness. Hence, the contributions of both design registration and exports can be considered as causes of the variation in design relatedness. However, the larger proportion of contribution from design registration indicates that the variation in design relatedness is influenced more significantly by design registrations in the overseas market rather than by exports.

4.5.2.5 Summary of Analysis on PVAR(1)

In the analysis of the PVAR(1) model, it is observed that design registration in overseas markets is predominantly influenced by its own past values, with the impact of design relatedness and exports playing a secondary role. The response of design relatedness to shocks is primarily driven by its own past values and design registrations, while the effect of shocks on design registrations is comparatively less significant. Similarly, the response of design registrations to shocks is primarily determined by its own past values, with a relatively smaller effect from design relatedness and exports. Exports, on the other hand, exhibit a positive response to shocks in design registration, although the effect is not as pronounced as the impact of design relatedness on exports. The Granger Causality Wald Tests indicate that design relatedness does not Granger-cause design registration, but there is Granger causality between design relatedness and exports, as well as between design registration and exports. The analysis of the forecast-error variance decomposition (FEVD) reveals that the variance of design registration is primarily influenced by its own shocks, with some contribution from design relatedness and exports. Similarly, the variance of exports is primarily affected by its own shocks, with some contribution from design registration and design relatedness. The variance of design relatedness is mainly influenced by its own shocks, with a significant contribution from design registration and a relatively smaller contribution from exports. In conclusion, the analysis provides valuable insights into the dynamic relationships between these variables and contributes to a comprehensive understanding of their interactions in the international design landscape.

4.5.3 Analysis on PVAR(2)

The PVAR(2) model, which incorporates a lag order of 2, is utilised in the analysis. The results are presented through IRF plots, Granger causality tests, and FEVD. The analysis is divided into parameter estimation, IRF plots, Granger causality tests, and FEVD. The parameter estimation results are presented in a regression results table. The IRF plots illustrate the impulse response of dependent variables to shocks from other variables and themselves. The Granger causality tests examine the causality among dependent variables. The FEVD analysis provides insights into the extent to which the variation of a dependent variable is affected by shocks from itself and other variables.

4.5.3.1 Parameter Estimation of PVAR(2)

In a similar manner to the parameter estimation of PVAR(1), the analysis is extended in the PVAR(2) model by incorporating a lag order of 2. This higher-order model enables the investigation of additional temporal dynamics and potential long-term effects. The parameter estimation results for the PVAR(2) model, utilising the same GMM estimator, are presented in Table 4.5. The instrumental variables employed in this estimation remain consistent with the untransformed values of each variable, resulting in a total of 18 instruments utilised in the modelling process. The inclusion of an additional lag order enhances the understanding of the relationship between dependent variables under investigation.

Group variable: ijk			Number of groups = 22549
Number of obs = 563725			Number of equations = 3
Number of instruments used: 18			AIC = 1.64451; BIC = 2.99395; HQIC = 2.02463
	Design Relatedness Density	Nbr. Design	Exports
Lag1. Design Relatedness Density	0.0532***	0.0020	0.0448**
	(0.0061)	(0.0090)	(0.0140)
Lag1. NbrDes	0.0304***	0.2551***	0.0417***
	(0.0021)	(0.0052)	(0.0091)
Lag1. Exports	0.0005	0.0110***	0.3085***
	(0.0003)	(0.0011)	(0.0047)
Lag2. Design Relatedness Density	0.0894***	-0.0722***	-0.0043
	(0.0064)	(0.0096)	(0.0147)
Lag2. NbrDes	0.0156***	0.2478***	0.0547***
	(0.0020)	(0.0052)	(0.0082)
Lag2. Exports	0.0005*	0.0087***	0.1777***
	(0.0002)	(0.0008)	(0.0040)
Instruments used:	Lag1 of Design Relatedness Density; Lag1 of Nbr. Design; Lag1 of Exports		
	Lag2 of Design Relatedness Density; Lag2 of Nbr. Design; Lag2 of Exports		
Hansen Test for over-identification:	Just identified - Hansen statistic is not calculated		
Note: Time effects have be demeaned, and All equations use the same set of Instruments. The model uses untransformed variables as instruments for the helmert-transformed variables in the model			

Table 4.5: Regression Results - PVAR(2)

4.5.3.2 IRF Results of PVAR(2)

The Impulse Response plots of the PVAR(2) model are depicted in Figure 4.13. These plots are generated using the calculated data extracted from the PVAR(2) model. The purpose of the impulse response analysis is to examine the influence of past values of dependent variables on other variables and themselves. It is important to note that the analysis of impulse response cannot solely rely on the coefficient estimates, as the impact of memory within the process is significant. Therefore, the utilisation of Impulse Response Functions and ribbon-line charts aids in visualising these impacts effectively.

Figure 4.13 illustrates the impulse response of various variables to shocks, including design relatedness, design registration, and exports. The first row represents the impulse response of design relatedness to shocks from itself, design registration, and exports.

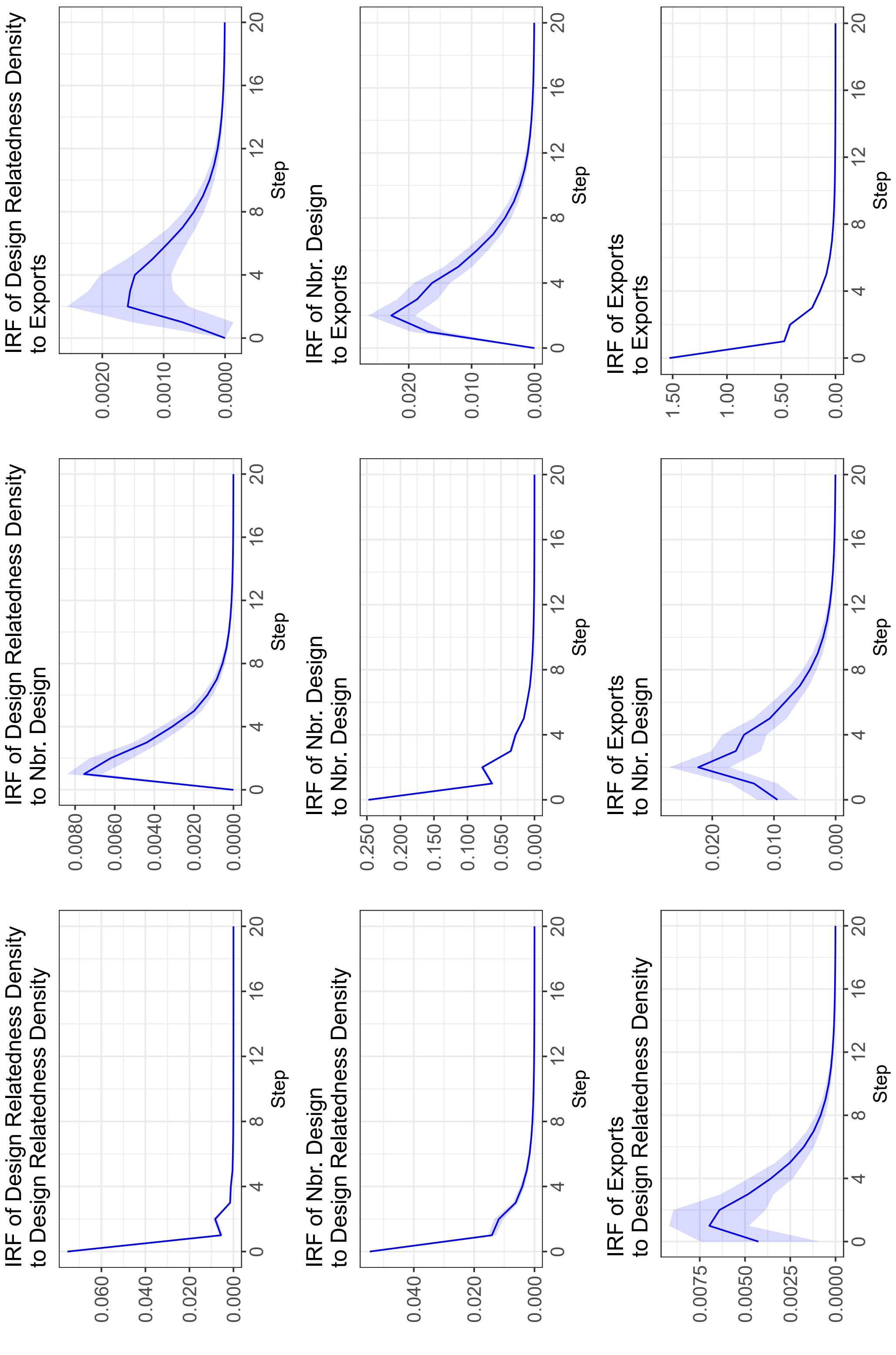


Figure 4.13: Impulse Response - PVAR(2)

The second row displays the impulse response of design registration to shocks from design relatedness, itself, and exports. Lastly, the last row depicts the impulse response of exports to shocks from design relatedness, design registration, and itself. A detailed analysis will be conducted separately for each subgroup within this figure. The impulse response of a dependent variable to shocks from itself will serve as a reference for comparison and further examination.

4.5.3.2.1 IRF Results of PVAR(2): Design Relatedness to Design Registration

The impulse response of design relatedness exhibits statistical significance and a positive relationship with shocks from design relatedness itself, design registration, and exports. However, the narrow error band observed in the impulse response of design relatedness to shocks from itself indicates a strong dependence on past values of design relatedness. Similarly, the impulse response of design relatedness to shocks from design registration is also positively identified at a high level of statistical significance. Notably, unlike the immediate response to shocks from design relatedness itself, design relatedness tends to exhibit a response to shocks from design registration after a lag of 1 period from the initiation of the shocks.

4.5.3.2.2 IRF Results of PVAR(2): Design Relatedness to Exports

The impulse response of design relatedness exhibits a larger magnitude in response to shocks from itself compared to shocks from the other two variables. However, both the effects of design registration and exports are statistically significant. In comparison to the shocks from exports, the impulse response of design relatedness tends to be larger in response to shocks from design registration. Furthermore, at period zero, design relatedness demonstrates a significant response to shocks from itself, while its response to shocks from the other two variables initiates from period 1. This indicates a lagged response of one order to shocks from the other two variables, with an immediate response observed only for shocks from itself.

4.5.3.2.3 IRF Results of PVAR(2): Design Registration to Design Relatedness

The observation of the impulse response of design registration to various shocks can be made from the second row of Figure 4.13. Similar to the impulse response of design relatedness to the shock of design registration, the impulse response of design registration to the shock of design relatedness also initiates from period zero. Furthermore, the most significant and largest response of design registration is still observed in response to shocks from itself. However, at this stage of the IRF analysis, it is premature to draw conclusions regarding the contribution proportion of different variables to the variation of a dependent variable. This aspect can be further discussed and analyzed in the subsequent FEVD analysis.

4.5.3.2.4 IRF Results of PVAR(2): Design Registration to Exports

In overseas markets, design registration is observed to exhibit a positive and significant response to shocks from exports. This implies that past exports, or in other words, previous export activities, may have an impact on future design registrations in overseas markets. Similarly to the response of design relatedness to shocks from exports, design registration tends to initiate its response to shocks from exports from period 1. This suggests a lagged response of one order to the initiation of the shock, unlike the immediate response of design registration to shocks from itself and design relatedness.

4.5.3.2.5 IRF Results of PVAR(2): Exports to Design Relatedness

The last row of Figure 4.13 presents the depiction of the impulse response of exports to shocks from other variables. The analysis reveals that exports are primarily influenced by shocks originating from itself. The impulse response of exports to shocks from itself exhibits the highest level of statistical significance and magnitude. Additionally, exports demonstrate a positive response to the variable of design relatedness, which is also statistically significant. In contrast to the impulse response of design relatedness or design registration to shocks from exports, the impulse response of exports to shocks from design relatedness initiates from period zero without any lags.

4.5.3.2.6 IRF Results of PVAR(2): Exports to Design Registration

In relation to the shock of design registration, a statistically significant and positive response is observed in exports. Furthermore, a comparison of the response magnitudes on the y-axis suggests that exports demonstrate a larger response to the shock of design registration compared to the shock of design relatedness. Hence, the analysis of the impulse response of exports to various shocks indicates an immediate response to shocks from all three variables, while maintaining a statistically positive nature. Moreover, exports respond to shocks in design registration and design relatedness starting from the initial period of the shocks.

4.5.3.3 Granger Causality of PVAR(2)

The Granger Causality Tests were conducted for the PVAR model with a lag of 2, utilizing a significance level of 0.05. When the p-values surpass this significance level, it can be concluded that the variables in the second column of Table 4.6 Granger-cause the variables in the first column. The null hypothesis states that the estimated coefficients of lagged variables in the second column of Table 4.6 are equal to zero. Based on this set of tests, it is observed that within the PVAR(2) model, the three dependent variables, namely design registration, design relatedness, and exports, Granger-cause each other. As Granger causality exists among any combination of two out of the three dependent variables, further analysis using the FEVD approach can be employed to assess the extent to which each variable is affected by itself and the other two variables.

Dependent Variable	Excluded	Chi-square	Degree of Freedom	p-Value
Design Relatedness Density	Nbr. Design	266	2	0.0000
Design Relatedness Density	Exports	20	2	0.0001
Design Relatedness Density	All	391	4	0.0000
Nbr. Design	Design Relatedness Density	60	2	0.0000
Nbr. Design	Exports	108	2	0.0000
Nbr. Design	All	182	4	0.0000
Exports	Design Relatedness Density	11	2	0.0041
Exports	Nbr. Design	45	2	0.0000
Exports	All	52	4	0.0000

Table 4.6: Granger Causality Wald Tests for PVAR(2)

4.5.3.4 Forecast-error Variance Decompositions (FEVD) of PVAR(2)

The Forecast Error Variance Decomposition (FEVD) of PVAR(2) employs a similar methodology to that of the FEVD for PVAR(1). The analysis is structured into three distinct groups, each corresponding to a specific dependent variable. In the initial stage, a comprehensive evaluation of the variance decomposition is conducted for each variable, encompassing both its own impact and the influences arising from other variables. This facilitates an assessment of the variable's susceptibility to self-influence as well as the effects exerted by the other variables.

Subsequently, the analysis proceeds by excluding the self-impact component and focusing on illustrating the impacts originating from the other two variables. This analytical step provides valuable insights into the relative contributions and influences of these variables within the PVAR(2) framework. By scrutinising the forecast error variance decomposition, a more profound comprehension of the interdependencies and causal relationships among the variables can be attained.

4.5.3.4.1 Forecast-error Variance Decompositions (FEVD) of PVAR(2): Design Registration

Figure 4.14 illustrates the Forecast Error Variance Decomposition (FEVD) of design registration using the PVAR(2) model. It is observed that the variation in design registration is primarily influenced by shocks originating from itself. Additionally, shocks in design relatedness and exports also contribute to the variation in design registration, albeit with a relatively smaller impact compared to shocks from design registration itself. Notably, shocks in design relatedness appear to have a more substantial effect on design registration compared to shocks from exports. However, due to the relatively small impact of both variables on the variation of design registration, it is not convenient to directly compare their effects within this figure.

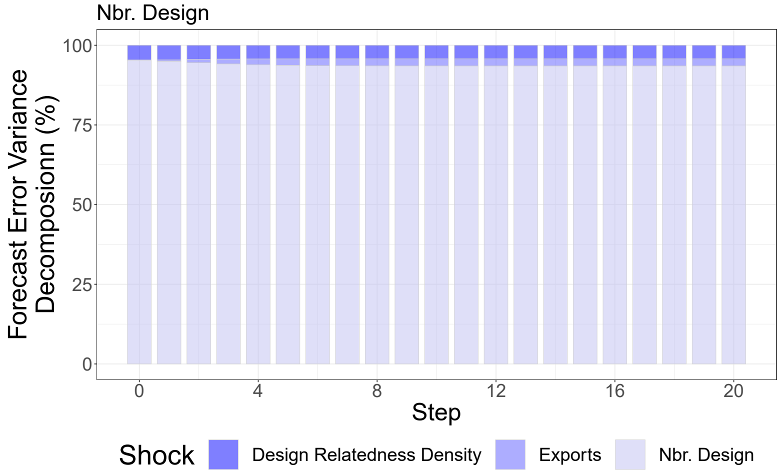


Figure 4.14: Forecast-error Variance Decompositions (FEVD) of Design Registration - PVAR(2)

The Figure 4.15 presents the Forecast Error Variance Decomposition (FEVD) of design registration, specifically focusing on the shocks of design relatedness and exports while excluding the contribution of the shock of design registration itself. It is observed that design relatedness impacts the variation of design registration starting from period zero, whereas exports begin to affect the variation of design registration from period 1. This suggests that compared to the contribution of design relatedness, exports exhibit a lag of one order in their impact on the variation of design registration.

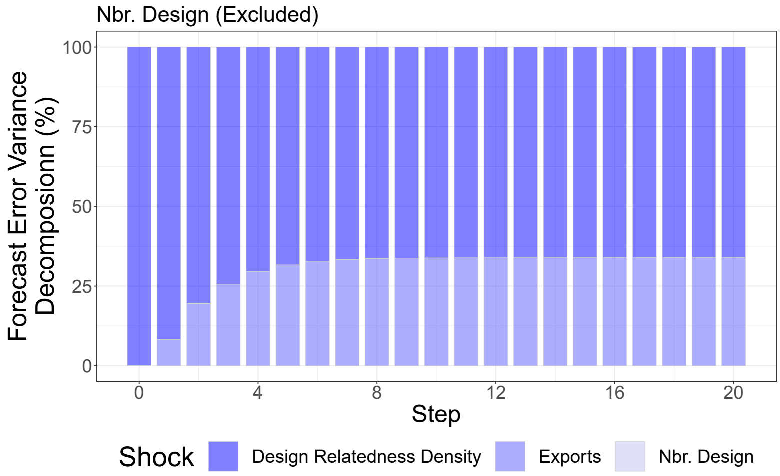


Figure 4.15: Forecast-error Variance Decompositions (FEVD) of Design Registration (Self-exclusion) - PVAR(2)

The results of the Granger Causality Tests for PVAR(2) indicate that design relatedness and exports are found to Granger-cause design registration in the overseas market. Therefore, it can be inferred that both design relatedness and exports play a role in influencing the variation of design registration, with design relatedness having a larger effect. Additionally, the impact of exports exhibits a lag of one order.

4.5.3.4.2 Forecast-error Variance Decompositions (FEVD) of PVAR(2): Exports

The FEVD results indicate that the largest effect on the variation of exports is attributed to exports itself. However, the impact of the other two variables is relatively small and not clearly depicted in Figure 4.16. Nevertheless, this does not imply that the contribution of the other two variables to the variation of exports can be disregarded. Granger causality tests reveal that both design registration and design relatedness can Granger-cause exports. Due to differing value ranges, these contributions cannot be easily observed in Figure 4.16. Consequently, when excluding the impact of exports on itself, the contributions of design relatedness and design registration to the variation of exports can be illustrated in Figure 4.17.

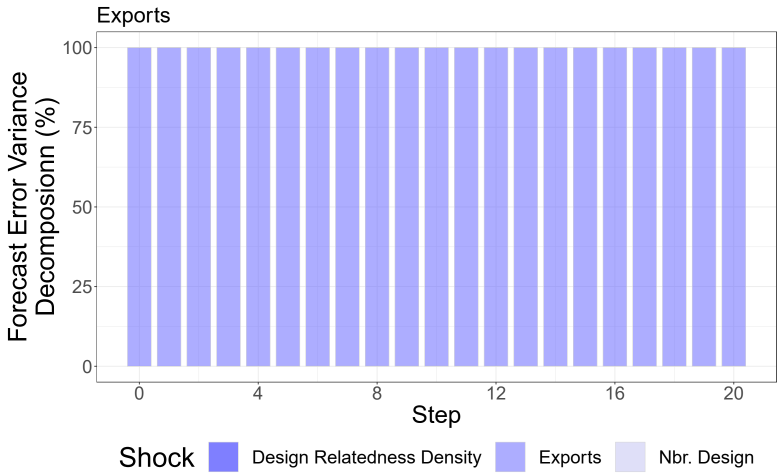


Figure 4.16: Forecast-error Variance Decompositions (FEVD) of Exports - PVAR(2)

Figure 4.17 illustrates that, excluding the impact of exports on itself, both design relatedness and design registration contribute to the variation of exports. Furthermore, a comparison between the contributions of shocks of design relatedness and design registration reveals that the number of design registrations has a greater impact on the variation of exports than the shocks of design relatedness. It is important to note that both design relatedness and design registration begin their contribution to the variation of exports from period zero, indicating that there are no lags in the response of exports to the shocks of design registration and design relatedness.

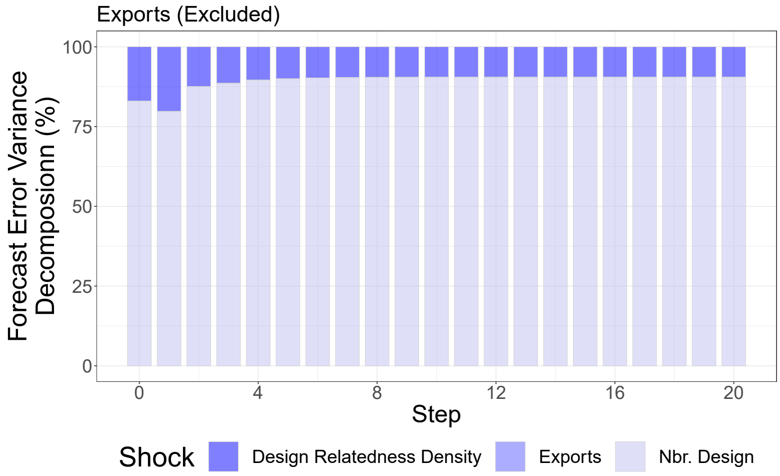


Figure 4.17: Forecast-error Variance Decompositions (FEVD) of Exports (Self-exclusion) - PVAR(2)

In conclusion, the causes of exports have been investigated to include both design relatedness and design registration. Therefore, the variation of exports is contributed to by design relatedness, design registration, and exports themselves. Furthermore, it is observed that exports tend to be more responsive to their own shocks compared to other shocks. When comparing the effects of design relatedness and design registration, it can be argued that the number of design registrations has a greater impact on exports, as opposed to design relatedness.

4.5.3.4.3 Forecast-error Variance Decompositions (FEVD) of PVAR(2): Design Relatedness Density

The variation of design relatedness is primarily influenced by shocks of the variable itself, as depicted in Figure 4.18. The shocks of the number of design registrations also contribute to the variation of design relatedness, but this contribution represents a small proportion of the overall variation. Additionally, Figure 4.18 does not clearly show the contribution of exports to the variation of design relatedness. Therefore, it is necessary to plot the decomposition of the variation of design relatedness after excluding its own impact.

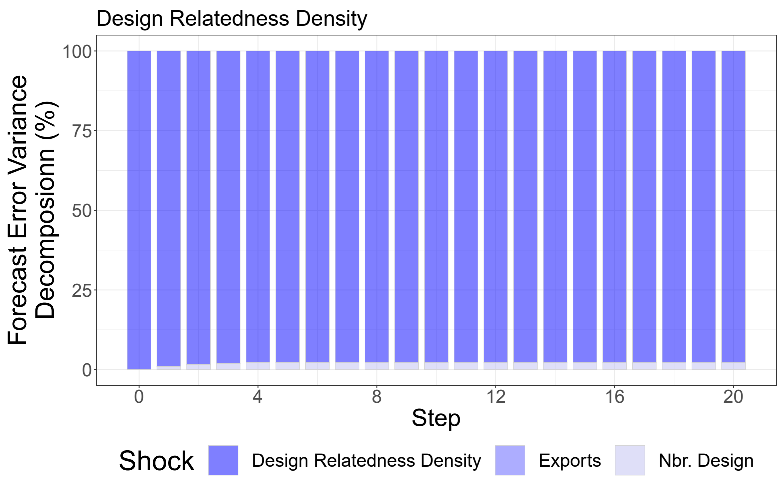


Figure 4.18: Forecast-error Variance Decompositions (FEVD) of Design Relatedness Density - PVAR(2)

The decomposition of variation, excluding the impact of design relatedness itself, is depicted in Figure 4.19. It is evident that both export and design registration contribute to the generation of design relatedness variation, with the shock of the number of design registrations having a greater effect. Additionally, the variation of design relatedness demonstrates an immediate response to the shock of design registration, starting from period zero without any lags. However, it exhibits a one-order lag in response to the shock of exports, starting from period one.

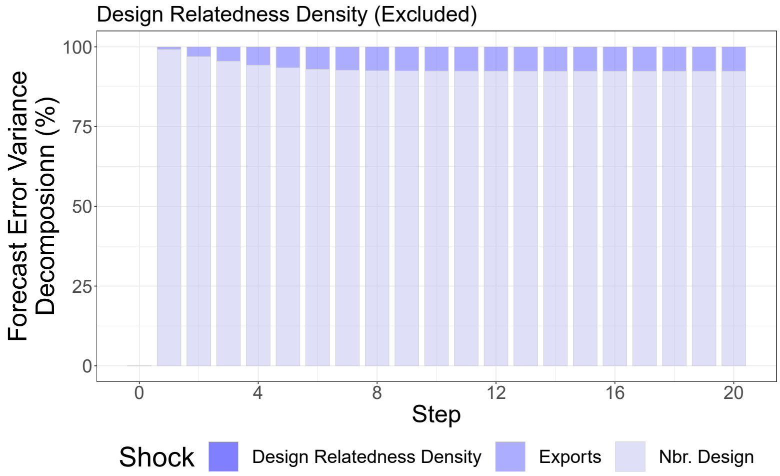


Figure 4.19: Forecast-error Variance Decompositions (FEVD) of Design Relatedness Density (Self-exclusion) - PVAR(2)

Considering the Granger Causality Tests, design relatedness is granger-caused by design relatedness itself, design registration, and export. Based on the FEVD results, it can be observed that design relatedness exhibits the largest response to its own shock. The second-largest response is attributed to the shock of design registration. Although the effect is relatively small, the variation of design relatedness is also influenced by the shock of export. In terms of timing, the response of design relatedness to shocks of itself and design registration begins immediately, while the response to shocks of export has a one-order lag.

4.5.4 Analysis on PVAR(3)

The results of the PVAR model with a lag order of 3 are presented in this section. Consistent with the previous analysis, this section is divided into the following subsections: parameter estimation, IRF analysis, Granger causality tests, and FEVD results. The parameter estimation subsection presents the estimates of parameters obtained from the PVAR model. The IRF analysis subsection examines the response of dependent variables to shocks from other variables and itself. This analysis helps determine whether past values of one variable have an effect on the future values of another variable. The Granger causality tests subsection statistically tests the relationship between impulse response and shocks presented in the IRF plots to determine if there is evidence of Granger causality. Finally, the FEVD results subsection aims to decompose the variance of a dependent variable to assess the contributions of other variables and itself to the variation.

4.5.4.1 Parameter Estimation of PVAR(3)

The coefficients are estimated based on the chosen model with a lag order of 3. Since the analysis is conducted using the Impulse Response Function, the section on coefficient or parameter estimation solely presents the details of the estimation and the estimated coefficients in Table 4.7.

Group variable: ijk			Number of groups = 22549
Number of obs = 541176			Number of equations = 3
Number of instruments used: 27			AIC = 1.62768; BIC = 3.02842; HQIC = 2.02292
	Design Relatedness Density	Nbr. Design	Exports
Lag1. Design Relatedness Density	0.0577***	0.0101	0.0269*
	(0.0064)	(0.0093)	(0.0135)
Lag1. NbrDes	0.0261***	0.2110***	0.0187*
	(0.0019)	(0.0047)	(0.0082)
Lag1. Exports	0.0001	0.0089***	0.2963***
	(0.0003)	(0.0011)	(0.0048)
Lag2. Design Relatedness Density	0.0936***	-0.0832***	-0.0119
	(0.0066)	(0.0096)	(0.0138)
Lag2. NbrDes	0.0121***	0.2186***	0.0330***
	(0.0017)	(0.0048)	(0.0074)
Lag2. Exports	0.0003	0.0061***	0.1440***
	(0.0002)	(0.0007)	(0.0038)
Lag3. Design Relatedness Density	0.0237***	0.0048	0.0245
	(0.0058)	(0.0090)	(0.0143)
Lag3. NbrDes	0.0218***	0.1672***	0.0132
	(0.0016)	(0.0040)	(0.0072)
Lag3. Exports	0.0001	0.0049***	0.1212***
	(0.0002)	(0.0006)	(0.0035)
Instruments used:			Lag1 of Design Relatedness Density; Lag1 of Nbr. Design; Lag1 of Exports
			Lag2 of Design Relatedness Density; Lag2 of Nbr. Design; Lag2 of Exports
			Lag3 of Design Relatedness Density; Lag3 of Nbr. Design; Lag3 of Exports
Hansen Test for over-identification:			Just identified - Hansen statistic is not calculated
Note: Time effects have be demeaned, and All equations use the same set of Instruments. The model uses untransformed variables as instruments for the helmert-transformed variables in the model			

Table 4.7: Regression Results - PVAR(3)

Hansen-J-Test is not applicable in this model, as the untransformed variables are used as instruments for the Helmert-transformed variables. It results in the just-identified model. Therefore, the Hansen-J-Test is not discussed here.

4.5.4.2 IRF Results of PVAR(3)

The IRF analysis of PVAR(3) reveals important insights into the relationship between design registrations, design relatedness, and exports. Figure 4.20 presents the IRF plots for PVAR(3), illustrating the impulse response of each dependent variable to shocks from other variables or itself. This analysis allows us to understand how these variables interact with each other over time. The x-axis represents the quarterly time periods used in this study, while the y-axis represents the impulse response of a dependent variable. Consistent with the findings from the previous analyses of PVAR(1) and PVAR(2), it is observed that all variables tend to exhibit the most significant and largest response to shocks from themselves. This suggests that each variable has a strong influence on its own dynamics. To provide a comprehensive understanding, each dependent variable will be analyzed separately in the following subsections.

4.5.4.2.1 IRF Results of PVAR(3): Response of Design Relatedness to Shock of Design Registration

The results from Figure 4.20 demonstrate that the shock of design registrations has a statistically significant positive impact on the design relatedness density, with significance assessed at the 95% confidence interval. This finding indicates that registering a design can positively influence the surrounding design relatedness densities, thereby providing greater advantages for the original design or other registered designs that share similarities.

Furthermore, the response of design relatedness reaches its peak at period 3, corresponding to the third quarter after the shock of new design registration. This suggests that design relatedness exhibits a positive response to new design registrations, with the maximum effect observed within one year. In practical terms, this implies that when

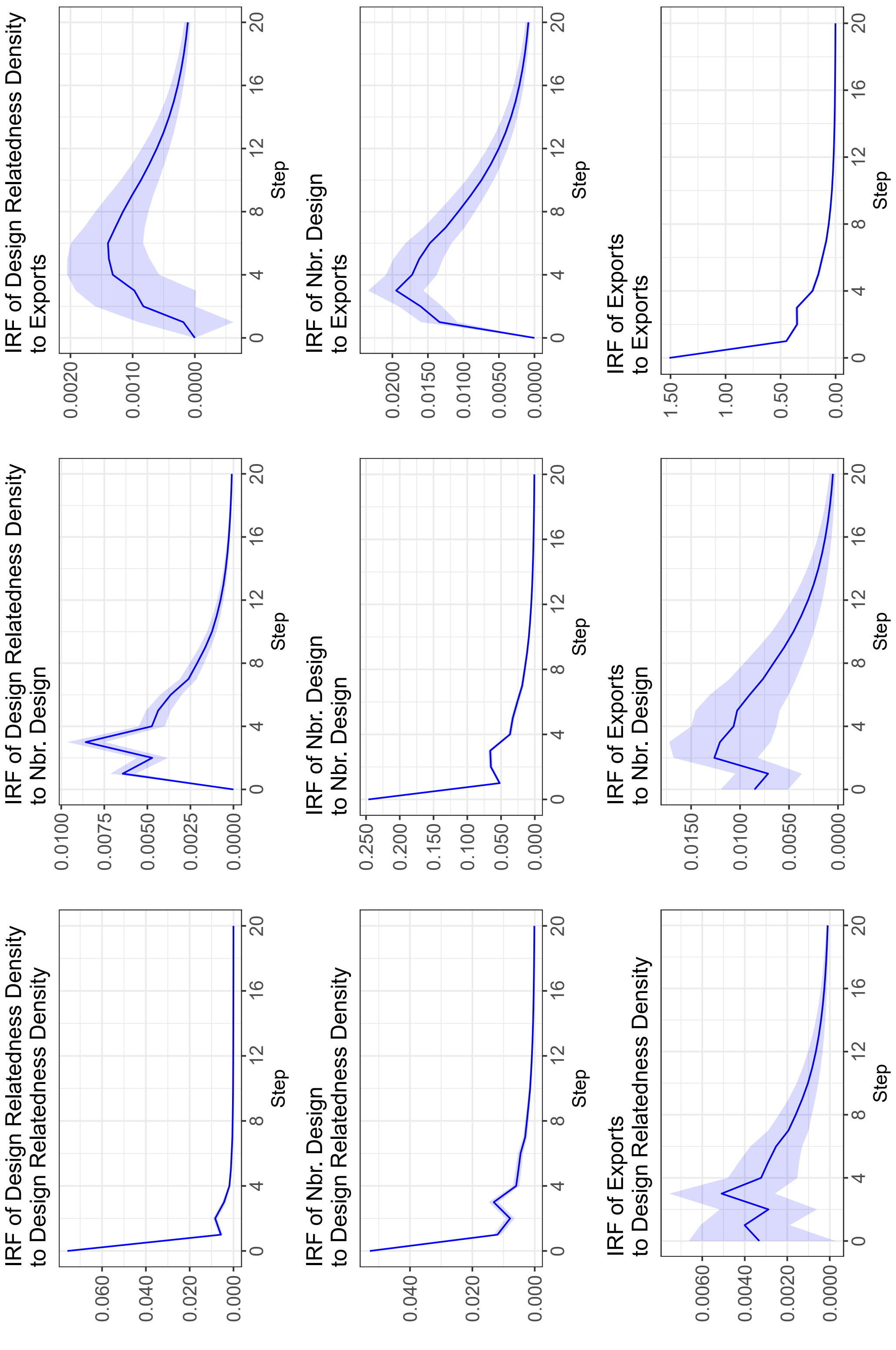


Figure 4.20: Impulse Response - PVAR(3)

there are existing design registrations in a particular region, design owners are more likely to register related designs to leverage the knowledge relatedness within that region for a specific commodity.

Subsequently, the response of design relatedness declines rapidly and converges to zero at period 16, marking the end of the second year following the shock of new design registration. Considering the timing of the maximum response, it can be inferred that design relatedness exhibits the highest response to the shock of design registration initially, but this response dissipates by the end of the second year.

4.5.4.2.2 IRF Results of PVAR(3): Response of Design Relatedness to Shock of Exports

Figure 4.20 illustrates that the design relatedness variable exhibits a positive response to the shock of exports, indicating that exports influence the design relatedness and drive designers to register designs in alignment with exported commodities. From a practical perspective, it can be inferred that exports directly contribute to the need for design registration, as exporters seek protection for their traded products.

The Impulse Response Function (IRF) analysis reveals that the response of design relatedness to an exports shock is not consistently significant. During the initial three quarters, the impact of the shock on design relatedness appears to be insignificant. However, from the end of the first year onwards, a statistically significant response becomes evident, with the maximum response occurring at the beginning of the second year following the shock.

Moreover, the response of design relatedness to the shock of exports gradually converges to zero by the end of the fourth year after the shock. Additionally, it is noteworthy that the significance of the response increases over time. This response pattern resembles the fluctuation observed in the response of design relatedness to the shock of new design registrations, suggesting that design relatedness can be influenced by both new design registrations and commodity exports.

4.5.4.2.3 IRF Analysis of PVAR(3): Response of Design Registration to Shock of Design Relatedness

As discussed before, design relatedness can be impacted by both new design registration and exports. From Figure 4.20, the response of design registration to the shock of design relatedness appears to be significant and positive overall. The response of design count to design relatedness was found to be extremely statistically significant, demonstrating that new design registrations are strongly affected by existing related design registrations in a particular region.

The response of design relatedness to the shock of new design registration can be seen to persist for four years, while the response of design registration to the shock of existing design relatedness is observed to diminish by the end of the third year following the shock. Consequently, it may be argued that design relatedness is a significant factor in the emergence of new design registrations, albeit with an effect that is not as long-lasting as in the reverse direction.

4.5.4.2.4 IRF Analysis of PVAR(3): Response of Design Registration to Shock of Exports

It is evident from Figure 4.20 that the variable *overseas design registration* yields a statistically significant, positive response to the shock of exports. This finding implies that export intention is an important factor for design owners to pursue legal overseas design protection. From the beginning of the response to the time point at which it disappears, the confidence interval remains positive, suggesting its statistical significance.

The response of new design registration to the shock of exports reaches its peak in the third quarter following the export shock, indicating that exporters have a rapid registration response for the involved designs when they start exporting. Subsequently, the response of the number of designs maintains a positive and significant value until the end of the fifth year. After this period, the response of design registration to the shock of exports begins to approach zero.

It may be argued that the response of design registration to the shock of exports is not as statistically significant as the response to the shock of design relatedness. Conversely, while design registration may provide a rapid but brief response to design relatedness, exports appear to have an extended influence on new design registrations in the long term.

4.5.4.2.5 IRF Analysis of PVAR(3): Response of Exports to Shock of Design Relatedness

Figure 4.20 demonstrates the positive, statistically significant response of exports to design relatedness shocks. This finding indicates that cross-sector design registrations can stimulate the export of related commodities, as reflected in measurements of design relatedness. Additionally, it is clear that the impulse response of exports exhibits a fluctuating trend until the response gradually dissipates.

It can be seen in the IRF figure that exports respond quickly to shocks of design relatedness, as indicated by the non-zero value observed during period 0. The confidence interval maintains a positive trajectory, indicating the potential for a positive response within the range of values. Consequently, it can be concluded that exports are capable of imparting a statistically significant and positive reaction to the shock of design relatedness at onset. This response is observed over a 4-year period following the initial shock of new design registration. In addition, the confidence interval of the response appears to be stable and more statistically significant at the beginning of the second year.

4.5.4.2.6 IRF Analysis of PVAR (3): Response of Exports to Shock of Design Registration

As can be seen in Figure 4.20, the response of exports to the shock of the number of designs is positive and significant, with no convergence to zero until the end of the fourth year. This indicates that registering design rights in foreign countries can promote corresponding exports.

The response of exports to the shock of the design count starts from period zero, which indicates that it is an instant response. Moreover, this response to one unit standard deviation of the design count shock does not converge to zero until the fourth year.

4.5.4.3 Granger Causality of PVAR(3)

Results from Granger causality Wald tests for Panel VAR are presented in Table 4.8. As discussed in the IRF analysis, all dependent variables seem to respond positively and significantly to the shock of the other two. However, while IRF can show the extent a variable can respond to another, it cannot precisely illustrate the causality between the variables. To gain greater insight into this relationship, the causal relationship between variables is explored utilizing the Granger causality test.

Dependent Variable	Excluded	Chi-square	Degree of Freedom	p-Value
Design Relatedness Density	Nbr. Design	288	3	0.0000
Design Relatedness Density	Exports	20	3	0.0002
Design Relatedness Density	All	447	6	0.0000
Nbr. Design	Design Relatedness Density	90	3	0.0000
Nbr. Design	Exports	76	3	0.0000
Nbr. Design	All	173	6	0.0000
Exports	Design Relatedness Density	8	3	0.0428
Exports	Nbr. Design	20	3	0.0002
Exports	All	26	6	0.0003

Table 4.8: Granger causality Wald tests - PVAR(3)

The results of the tests indicate a mutual causal relationship between design-relatedness density and the number of designs. Significance was found for both null hypotheses testing whether design-relatedness does not Granger-cause design count, and vice versa. Additionally, exports were discovered to have reciprocal effects on both design-relatedness density and the number of designs, implying that these two variables can both Granger-cause exports, as well as be caused by them.

Analysis revealed a comparatively weak but nonetheless statistically significant association between exports and design-relatedness, which, comparatively, showed lower statistical significance than other tests. Upon further inspection, all variables were found to be significantly associated with each other, where any combination of two variables of these three variables has a two-way causal relation.

4.5.4.4 Forecast-error Variance Decompositions (FEVD) of PVAR(3)

The preceding section has examined the response of each variable to shocks from other variables and discussed how this response varies over time. It has also confirmed the presence of mutual causality among the three variables. This section aims to further investigate the underlying causes of each variable to determine the primary driver for each one. Based on the analysis of FEVD in PVAR(1) and PVAR(2), it has been found that the most significant and largest effect on the variation of a dependent variable comes from the variable itself. Therefore, the FEVD analysis on PVAR(3) will present both the complete FEVD, including all variables including the variable itself, and a partial FEVD that excludes the given dependent variable.

4.5.4.4.1 Forecast-error Variance Decompositions (FEVD) of PVAR(3): Number of Design

The complete decomposition of variance for design registration, incorporating shocks of design registration, design relatedness, and export, is depicted in Figure 4.21. The analysis reveals that the variability in design registration is predominantly driven by shocks originating from design registration itself, as opposed to shocks associated with design relatedness and export. However, due to the relatively minor numerical contribution of shocks stemming from design relatedness and export, their impact is not clearly discernible in this figure. To address this, a partial decomposition of design registration variance is illustrated in Figure 4.22.

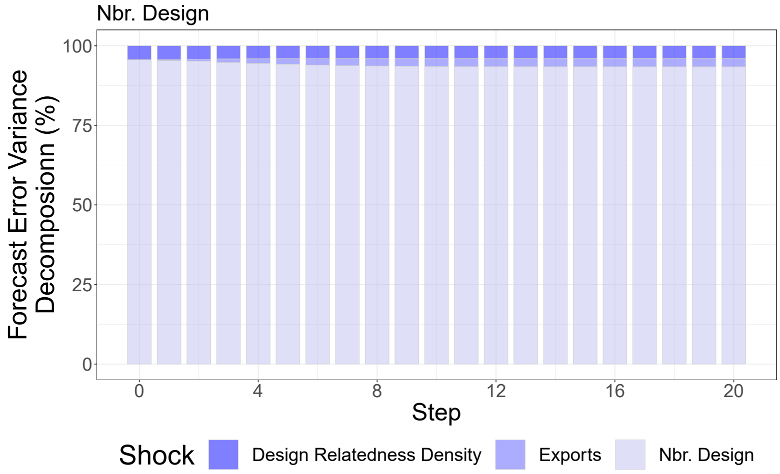


Figure 4.21: Forecast-error Variance Decompositions (FEVD) of Nbr. Design - PVAR(3)

The significance of design relatedness and exports in influencing the number of design registrations is evident from the analysis depicted in Figure 4.22. Notably, the disparities in the impact of shocks from different variables on the variation of design registration are clearly observed in Figure 4.22, whereas such distinctions are not clearly visible in Figure 4.21.

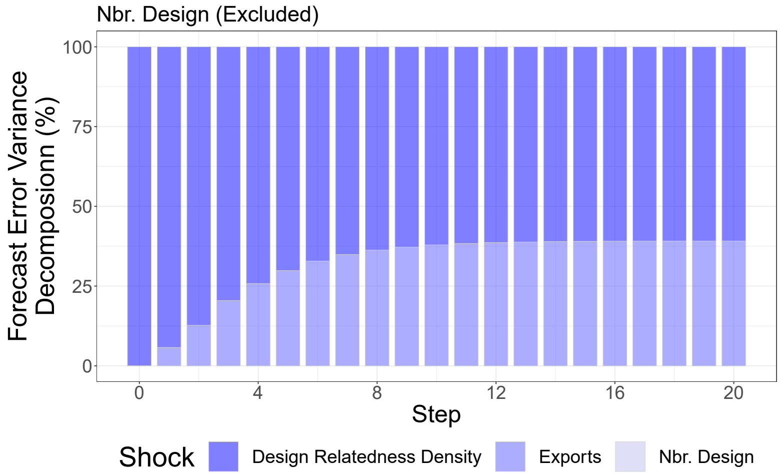


Figure 4.22: Forecast-error Variance Decompositions (FEVD) of Nbr. Design - PVAR(3)

Therefore, the role of design relatedness and exports in influencing the variation of design registrations is demonstrated by the findings presented in Figure 4.22. Specifically, it is apparent that the response of the number of designs is predominantly influenced by the density of design relatedness at period 1, indicating a delayed impact of exports on the number of designs. Moreover, the explanatory power of design relatedness density diminishes over time, whereas the explanatory power of exports increases. In the long run, both variables contribute to elucidating the number of design registrations, with exports accounting for approximately 40% and design relatedness accounting for 60%.

4.5.4.4.2 Forecast-error Variance Decompositions (FEVD) of PVAR(3): Exports

The contribution of shocks from design registration and design relatedness to the forecast error variance decomposition (FEVD) of exports, as depicted in Figure 4.23, is too small to be discernible. However, previous analyses including impulse response function (IRF) analysis and Granger causality tests indicate that both design registration and design relatedness variables have a causal relationship with exports. Hence, it is inappropriate to simply conclude that exports are solely influenced by their own past values. To provide further insights, a partial FEVD of exports is conducted and presented in Figure 4.24.

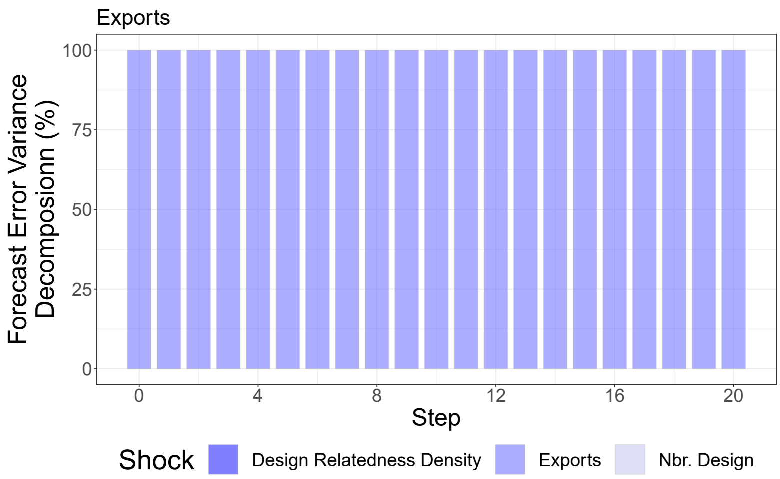


Figure 4.23: Forecast-error Variance Decompositions (FEVD) of Exports - PVAR(3)

Based on Figure 4.24 and the results of Granger Causality Tests, it can be inferred that both the number of design registrations and design relatedness are influenced by exports. Additionally, the variable of exports exhibits an immediate response to both of the other two variables at period 0.

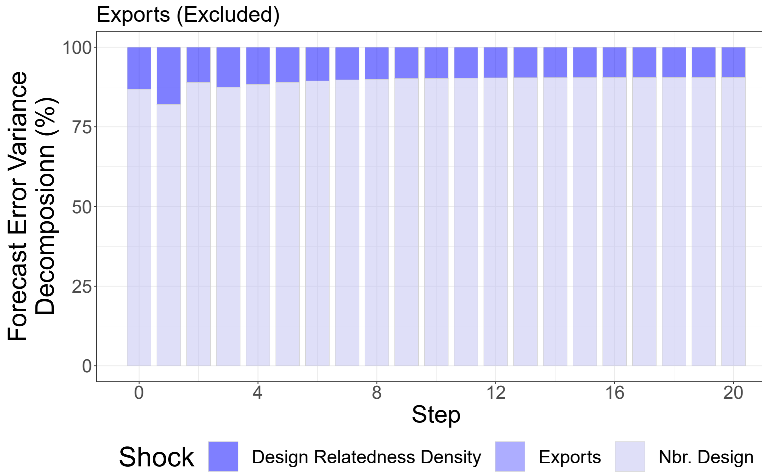


Figure 4.24: Forecast-error Variance Decompositions (FEVD) of Exports (Self-exclusion) - PVAR(3)

Moreover, it is observed that the shocks of design registration have a greater influence on the variation of exports compared to the shock of design relatedness. These observations indicate that the variability of exports is influenced by shocks originating from exports itself, design registration, and design relatedness. Consequently, the impact of past values of exports is more significant than the impact of the other two variables. Furthermore, when comparing the effects of design registration and design relatedness, it can be concluded that design registration has a numerically larger effect on the variation of exports.

4.5.4.4.3 Forecast-error Variance Decompositions (FEVD) of PVAR(3): Design Relatedness

The FEVD analysis of design relatedness indicates that the variation of design relatedness is primarily influenced by shocks originating from itself. Additionally, design registration also makes a relatively small numerical contribution to the variation of design relatedness. However, the impact of export shocks on the variation of design relatedness is not clearly evident in the figure, possibly due to the different value ranges of these three variables. Considering the findings from the IRF results and Granger Causality Tests, which suggest that design relatedness can be influenced not only by itself and design registration but also by exports, a partial FEVD of design relatedness excluding its self-impact is performed and presented in Figure 4.26.

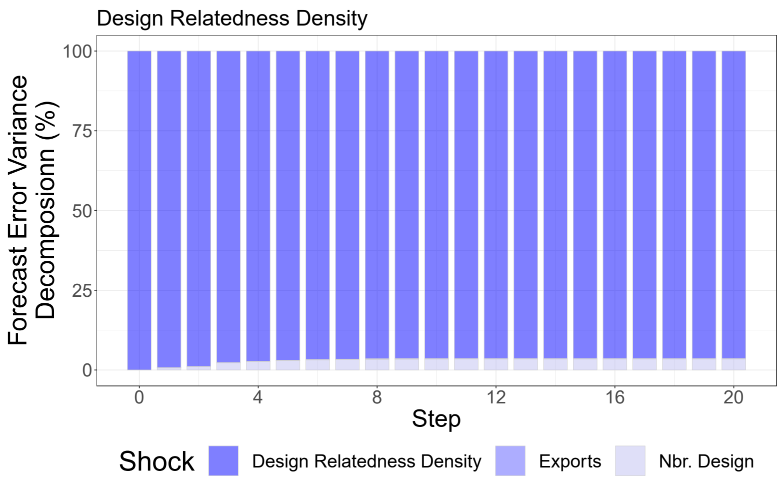


Figure 4.25: Forecast-error Variance Decompositions (FEVD) of Design Relatedness - PVAR(3)

Figure 4.26 demonstrates that both the number of design registrations and exports influence the density of design relatedness. However, upon comparing the contributions of these variables, it becomes evident that the variation in design relatedness is primarily driven by shocks originating from design registration, rather than exports. Notably, during the initial time periods, the variable of exports has no contribution to the response of design relatedness.

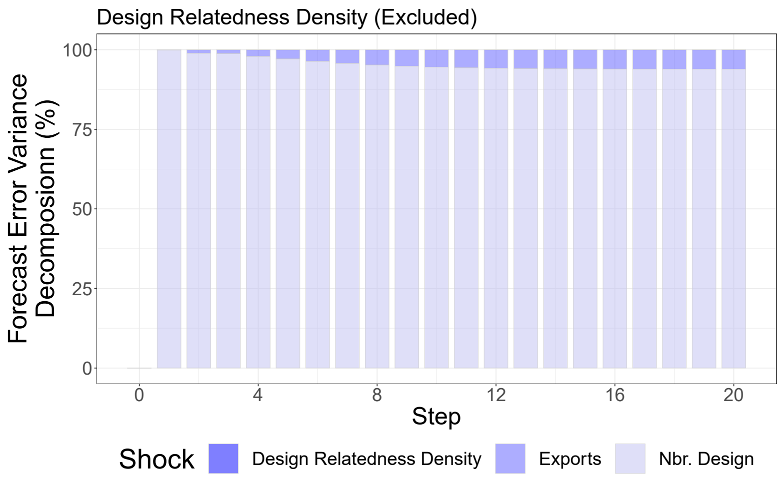


Figure 4.26: Forecast-error Variance Decompositions (FEVD) of Design Relatedness (Self-exclusion) - PVAR(3)

Furthermore, there is a notable increase in the impact of exports over time. This is supported by the IRF plots and Granger Causality Tests, which suggest that exports are a causal factor for design relatedness. Although the contribution of export shocks is numerically small, it implies that the shock of exports can influence design relatedness. In conclusion, the variation of design relatedness can be influenced by shocks from itself, design registration, and exports. Among these factors, design relatedness itself has the largest numerical effect, while design registration tends to have a greater impact on the variation of design relatedness compared to export shocks.

4.5.5 Summary of IRF Analysis

Overall, the impulse response analysis of the PVAR(1), PVAR(2), and PVAR(3) models provides valuable insights into the relationships between design registrations, design relatedness, and exports. The results indicate that design registrations in foreign countries have a positive and significant impact on exports, with the effects lasting for up to four years. The response of exports to the shock of design count is immediate and does not converge to zero until the end of the fourth year. Additionally, the analysis reveals that design relatedness plays a crucial role in influencing design registrations and exports, with each variable exhibiting significant responses to shocks from the other variables. However, further analysis through variance decomposition is necessary to fully understand the contribution of each variable to the overall variation.

4.5.5.1 Impulse Response of Design Relatedness

The impulse response of design relatedness to various shocks is depicted in the first row of Figure 4.27 for different lag orders of PVAR models. It is evident that the most statistically significant and substantial response of design relatedness is observed when it is subjected to shocks from itself. When comparing the impulse responses of design relatedness to shocks from design registration and exports, it can be concluded that

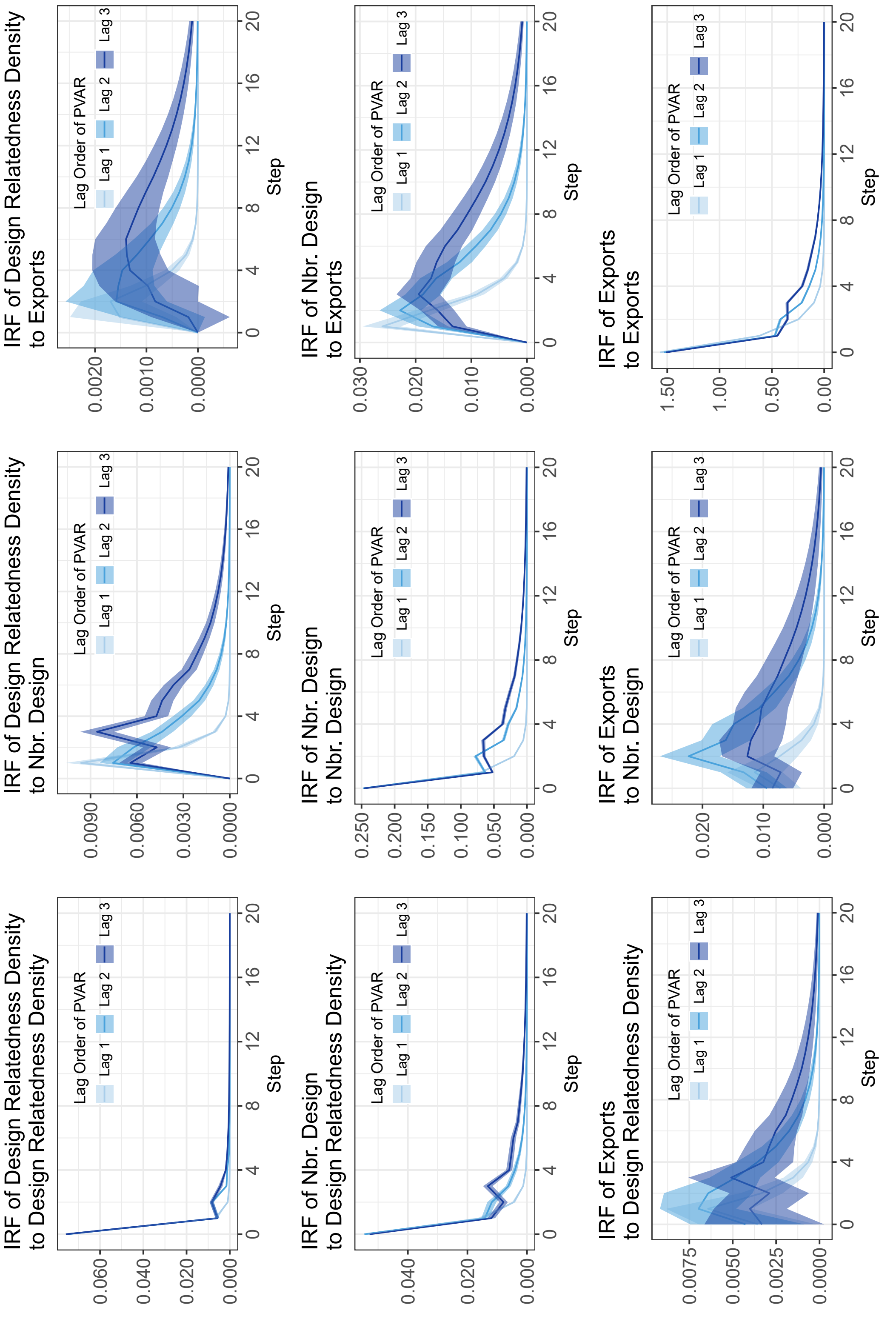


Figure 4.27: Summary of Impulse Response: PVAR(1), PVAR(2), and PVAR(3)

design relatedness tends to exhibit a more pronounced and larger response to shocks from design registration, as opposed to the response to shocks from exports. This finding remains consistent across different lag orders of PVAR.

On the other hand, it is observed that the impulse responses of design relatedness to shocks of design registration and export have a longer duration compared to the shocks from itself. This can be seen from the convergence of the IRF lines of design relatedness to shocks of design registration and export to zero at a later period, in contrast to the IRF lines of design relatedness to shocks from itself. The variation in lag orders of PVAR does not affect this observation.

Additionally, the impulse response of design relatedness exhibits a consistent starting point across different lag orders of PVAR. The response of design relatedness commences at period zero without any lags when subjected to shocks from itself. However, when responding to shocks from design registration and export, the response of design relatedness initiates from period 1, indicating a one-order lag.

Nevertheless, variations exist among different lag orders implemented in the PVAR analysis. It is observed that when a lag order of 3 is employed, the impulse response of design relatedness tends to have a longer duration for shocks from any variables compared to lag orders of 1 or 2. Conversely, when a lag order of 3 is utilized, the error band widens in comparison to using lag orders of 1 or 2. However, at a 95%

confidence interval, all the responses remain on the positive side of the y-axis, indicating that despite the wider error bands, the results are still significantly positive.

4.5.5.2 Impulse Response of Design Registration

The impulse response analysis of design registration reveals that when subjected to shocks from itself, design registration exhibits the most statistically significant and largest response. Comparing the impulse responses of design registration to shocks from design relatedness and exports, it can be concluded that design registration tends to have a more statistically significant and larger response to shocks from design relatedness compared to shocks from exports. This consistent pattern holds true across different lag orders of PVAR.

Furthermore, the impulse response of design registration to shocks from exports tends to have a longer duration compared to the response to shocks from itself and design relatedness. The response of design registration to shocks from design relatedness does not exhibit a significant difference in duration compared to the response to shocks from itself. This observation is based on the time period at which the impulse response converges to zero, and it remains consistent across different lag orders.

Moreover, as depicted in the second row of Figure 4.27, design registration tends to initiate its response to shocks from itself and design relatedness from period zero, indicating no lags in these responses. Conversely, the impulse response of design registration to shocks from exports initiates from period 1, suggesting a one-order-lagged response to export shocks.

The choice of lag order in PVAR analysis introduces differences in two aspects: the response duration of design registration and the width of the error band. It is observed that for all responses of design registration to any shocks in PVAR(3), the response duration is longer compared to the other two lag orders. Additionally, the error band of the response of design registration to different shocks widens as the lag order increases from 1 to 3.

4.5.5.3 Impulse Response of Export

The third row of Figure 4.27 displays the impulse response of exports as determined by PVAR models with different lag orders. It is evident that all the impulse responses of exports to different shocks are statistically significant and positive, as the error band is positioned above the x-axis. Notably, the most statistically significant and numerically largest response of exports is observed when it is subjected to shocks from itself. When comparing the responses of exports to shocks from both design registration and design relatedness, it is apparent that the response of exports tends to be numerically larger to the shock of design registration than to the shock of design relatedness.

Furthermore, in comparison to the impulse response of exports to shocks from itself, it can be observed that the impulse response of exports tends to have a longer duration for unit shocks of design registration and design relatedness. Consequently, although exports exhibit the most significant and largest response to shocks from itself, the duration of this response is shorter than its response to shocks from design relatedness and design registration.

Additionally, the impulse response of exports does not exhibit any lags when responding to shocks, including exports itself, design registration, and design relatedness. This finding remains consistent when different lag orders of PVAR are employed. In contrast to the design variables, exports tend to respond immediately to shocks, while design relatedness demonstrates a one-order lag in response to shocks from exports and design registration, and design registration exhibits a one-order lag in response to shocks from exports.

The utilization of different lag orders in PVAR analysis introduces variations in the impulse response of exports. It is observed that as the lag orders increase, the error band, with a 95% confidence interval, becomes wider. Moreover, in terms of response duration, as the lag orders increase, the response of exports can persist for a longer period.

4.5.6 Summary of Granger Causality Tests

The parameter estimation provides regression outcomes, while the IRF plots illustrate the influence between variables. However, the impulse response alone cannot confirm the existence of causality between the variables of overseas design registration, overseas design relatedness, and exports. To address this, Granger Causality Wald Tests are employed.

Table 4.4 presents the results of the Granger causality test for PVAR(1). The null hypothesis states that the variables in the second column of Table 4.4 do not Granger-cause the variables in the first column. Rejecting the null hypothesis indicates that the variables in the second column have a significant Granger-causal effect on the variables in the first column. At a significance level of 0.05, it is evident that design relatedness does not Granger-cause design registration. However, Granger causality is identified between other pairs of variables. These findings complement the IRF analysis and can be further explored in the context of Forecast-Error Variance Decompositions.

Similarly, Granger Causality Tests are conducted for the PVAR model with a lag of 2, using a significance level of 0.05. Table 4.6 presents the results. Here, the null hypothesis assumes that the estimated coefficients of lagged variables in the second column equal zero. The tests reveal that within the PVAR(2) model, design registration, design relatedness, and exports Granger-cause each other. As Granger causality exists among any combination of two out of the three dependent variables, further analysis using the FEVD approach can assess the impact of each variable on itself and the other two variables.

Additionally, Table 4.8 displays the results of Granger causality Wald tests for Panel VAR. While the IRF analysis suggests positive and significant responses of all dependent variables to shocks from the other two, it does not provide a precise indication of causality. The Granger causality tests reveal a mutual causal relationship between design relatedness density and the number of designs. Furthermore, exports exhibit reciprocal effects on both design relatedness density and the number of designs, indicating that these variables can both Granger-cause exports and be caused by them.

Dependent Variables	Causes of Dependent Variables (Granger) by PVAR(1)	Causes of Dependent Variables (Granger) by PVAR(2)	Causes of Dependent Variables (Granger) by PVAR(3)
Design Relatedness	Design Relatedness; Design Registration; Export	Design Relatedness; Design Registration; Export	Design Relatedness; Design Registration; Export
Design Registration	Design Registration; Export	Design Relatedness; Design Registration; Export	Design Relatedness; Design Registration; Export
Export	Design Relatedness; Design Registration; Export	Design Relatedness; Design Registration; Export	Design Relatedness; Design Registration; Export

Table 4.9: Summary of Granger Causality Wald Tests by PVAR(1), PVAR(2), and PVAR(3)

In summary, the Granger causality tests provide insights into the causal relationships between the variables. They confirm the presence of causality among the variables, with various pairs exhibiting two-way causal relations. These findings enhance our understanding of the dynamics between design registration, design relatedness, and exports. Granger Causality Tests of PVAR(1), PVAR(2), and PVAR(3) are summarised in Table 4.9. For PVAR(2) and PVAR(3), all variables, including design registration, design relatedness, and exports, are identified as having mutual Granger causality. However, design relatedness is not identified as the Granger cause of design registration in PVAR(1).

4.5.7 Summary of FEVD

The Forecast-Error Variance Decomposition (FEVD) analysis of dependent variables in different lag order PVAR models yields consistent results. Firstly, all PVAR models indicate that the largest effect on the variation of a dependent variable comes from itself. This observation is clearly demonstrated in the FEVD bar chart, which includes all shocks, including the dependent variable itself. Consequently, to compare the contribution of the other two variables to the variation of a given dependent variable, it is necessary to observe the FEVD bar chart while excluding the contribution of the dependent variable itself.

Regarding the variation of design registration, PVAR models with lag orders of one, two, and three suggest that both design relatedness and export can influence the variation of design registration. However, the shocks of design relatedness tend to have a larger effect compared to the shocks of export on design registration. The effect of design relatedness initiates at period zero, while the effect of export on design registration exhibits a one-order lag, starting from period one. This observation remains consistent across different lag order PVAR models.

The variation of export is influenced by shocks from itself, design relatedness, and design registration. The largest contribution to the variation comes from shocks of itself. Comparing the effects of design relatedness and design registration, it is evident that the contribution of design registration is numerically larger than the contribution of design relatedness to the variation of export. This finding is observable in the FEVD results from PVAR models with different lag orders.

Similarly, the variation of design relatedness is affected by shocks from itself, design registration, and export. The effect of shocks from itself has the largest numerical contribution to the variation. On the other hand, design registration and export contribute to the variation of design relatedness to different extents. Shocks from design registration have a larger contribution, while the contribution from shocks of export is relatively small. This observation holds true across all PVAR models with different lag orders.

4.6 Discussion

This investigation employs the UK regional panel to examine the interdependencies among overseas design relatedness, overseas design registration, and exports using the PVAR approach. The impulse response function (IRF) plot demonstrates the significant role of each variable in promoting the other two. Additionally, the Granger causality test confirms the mutual causality among these three variables. The analysis using the forecast error variance decomposition (FEVD) reveals that: (i) design relatedness and exports have a significant influence on the number of design registrations, with design relatedness exerting a larger effect; (ii) the number of design registrations and design relatedness are significant drivers of exports, with design registration being the more influential factor; (iii) the number of design registrations overseas and exports significantly affect overseas design relatedness, with overseas design registration contributing more substantially than exports. These observations will be discussed in further detail in the following subsections.

4.6.1 Interdependencies of Overseas Design Relatedness, Overseas Design Registration, and Exports

The mutual causality among design relatedness, design registration, and exports is confirmed in this study. This confirmation is based on the analysis of PVAR models with lag orders ranging from 1 to 3. The impulse response to shocks among different dependent variables can be illustrated through the IRF plots, while the causal relationship between these responses and shocks is examined using the Granger Causality Tests. In this section, these interdependencies will be further explored by discussing them in three combinations of any two variables: (i) the interdependencies of overseas design registration and design relatedness; (ii) the interdependencies of overseas design relatedness and exports; (iii) the interdependencies of overseas design registration and exports.

4.6.1.1 Interdependencies of Overseas Design Registration and Overseas Design Relatedness

The interdependencies between overseas design registration and overseas design relatedness suggest a mutual influence between these variables. This study is pioneering in exploring this interaction effect within the broad concept of knowledge relatedness and new knowledge generation. Previous research has examined the correlation between knowledge relatedness and the number of technologies, but this has often been discussed in terms of temporal increase (Kogler et al., 2013). The PVAR approach with fixed effects eliminates the time effect, revealing the interaction effect between these variables. Furthermore, the interdependency has passed the Granger causality test, suggesting mutual causality rather than mere interaction.

This research also discusses the interdependencies from the perspective of industrial design, an important type of patent that has not been sufficiently investigated in current research. The drivers of industrial design, particularly those registered overseas, are not well understood. Design is often seen as a component of firm innovation that can enhance firm performance, including export performance. Keebaugh (2005) suggested that industrial design should be considered as intellectual property and an innovation outcome (Candi and Gemser (2010)), which is a component of the intangible economy (Corrado, Haskel, Jona-Lasinio and Iommi (2022)). Investigating the drivers of industrial design can contribute to research on intangible economic growth.

4.6.1.2 Interdependencies of Overseas Design Relatedness and Exports

The results indicate that design relatedness generated in the overseas market interacts with exports. As this interaction passes the Granger causality test, it can be inferred that both design relatedness generated in the overseas market and exports mutually influence each other. Knowledge relatedness has been extensively discussed in current research as a key driver of new knowledge generation, economic growth, and exports (Balland, Boschma et al., 2019; Boschma et al., 2012; Kogler et al., 2013). However, the perspective of the design knowledge network, computed by design relatedness, has not been explored. This study provides the first empirical evidence of the promoting role of design knowledge relatedness in exports.

The reverse causality of design relatedness and exports supports the theory of learning by exports (de Loecker, 2013; Lööf et al., 2015; Salomon and Shaver, 2005) from the aspect of industrial design. This research is unique in its empirical discussion of design within the context of the learning by exports theory. The findings suggest that exporters can seek new knowledge regarding not only technologies but also the appearance of articles. Exporters exposed to the foreign market can access both new technologies and the aesthetic preferences in the foreign market. Exposure to new technologies can drive the development of products using these technologies, while adjusting the aesthetics according to the preferences of local markets can reshape existing technologies into a novel appearance that captures market preference.

4.6.1.3 Interdependencies of overseas design registration and exports

This study discusses the interaction effect between design registration and design relatedness, focusing on designs registered overseas. Therefore, this study also examines intellectual property protection in the overseas market and export performance. A review of the literature reveals extensive research on the impact of overseas intellectual property rights (IPR) protection on exports (W.-H. Liu and Lin, 2005). Many papers suggest that exporting is a motive for firms to apply for overseas patents. However, there is a lack of empirical research investigating the interrelationship between overseas patent registration and exports. This study fills this gap from the perspective of design patents.

The application of the PVAR approach and Granger causality test enables the exploration of the mutual causality effect between overseas design registration and exports. Additionally, the FEVD method allows the comparison of the effects of the other two variables on a given variable. Therefore, in cases where both other variables cause a given variable, their differences can also be analyzed. This will be further discussed in the next section.

4.6.2 Drivers of: Overseas Design Registration, Design Relatedness, and Exports

The results of the FEVD analysis suggest mutual causality among the three variables. In other words, both overseas design relatedness and exports cause overseas design registration, both overseas design registration and exports cause overseas design relatedness, and both overseas design registration and overseas design relatedness cause exports. Moreover, the drivers of overseas design registration and overseas design relatedness start their effects one period later after the variables receive the shock.

4.6.2.1 Drivers of New Design Registration

Both overseas design relatedness and exports drive new design registration in the overseas market. The driving role played by overseas design relatedness can be explained by the theory of knowledge relatedness. Tanriverdi and Venkatraman (2005) suggested that related knowledge resources can complement each other, enriching the single knowledge fields covered by them. This is the rationale for why overseas design relatedness can drive new design registration in the overseas market. On the other hand, the promoting role of exports in overseas design registration can be explained from the perspective of exporter firms' motivation. Existing research suggests that exporting intention is a significant influencing factor for international patenting behavior (Zhang et al., 2022). Exporter firms involved in innovation activities face the threat of counterfeiting, and the enforcement of intellectual property protection can mitigate this risk (C.-H. Yang and Kuo, 2008). Therefore, firms are motivated by exporting intentions or existing exporting activities to apply for cross-country intellectual property rights to reduce uncertainty and risks.

Furthermore, as presented in the FEVD results, design relatedness plays a more significant role than exports in overseas new design registration. This suggests that the driving force of knowledge relatedness is stronger than exports in promoting overseas design registration. While this is not well-supported by empirical evidence in current research, a large body of literature suggests that knowledge relatedness is a key driver of exports and economic growth (Balland, Boschma et al., 2019; Boschma et al., 2012; Kogler et al., 2013). Considering the results of this study in the context of theories from existing research, it can be inferred that knowledge relatedness is the root cause of both knowledge generation and economic growth. Therefore, compared to exports, another driving force of overseas design registration, overseas design relatedness can promote overseas design registration more significantly.

4.6.2.2 Drivers of Design Relatedness Generation

According to the results of the IRF analysis and the Granger causality test, both the number of overseas design registrations and exports are drivers of the generation of design relatedness in the overseas market. Before discussing the rationale for this fact, several points are worth mentioning. First, as demonstrated in the measures and data section, the computation method of design relatedness is based on the number of cross-sectoral designs, so there must be an association between the number of designs and design relatedness. Second, exports have been illustrated as a driver of the number of design registrations in the overseas market. Considering the association between the number of designs and design relatedness, theoretically, it should also be associated with design relatedness. These two points are analyzed based on the measurement method adopted in this study and will be further discussed in the context of existing research.

Existing research has argued that knowledge relatedness is a key driver of new knowledge generation (Balland, Boschma et al., 2019), which is the rationale for knowledge growth. Both patents and industrial designs are creations or inventions (WIPO, 2023c), and intellectual property is a kind of intangible capital in businesses as well as the value of ideas (Ewens et al., 2019). When it can be classified into different sectors, it can be identified as cross-sectoral or cross-class knowledge (Kogler et al., 2013). Therefore, knowledge itself is the origin of knowledge relatedness. In addition to the explanation of the measurement method of design relatedness, the logic discussed here is the theoretical reason that overseas design registration can drive the design relatedness generated in the overseas market.

On the other hand, besides the association relationship between exports and overseas design registration, which suggests that exports affect overseas design relatedness by motivating firms to register new designs in the overseas market, exporting activity is also a direct driver of overseas design relatedness. Exporting activities provide opportunities for exporter firms, and in order to maintain competitiveness in the global market, exporters would like to hold cross-sectoral intellectual property rights in the global market. In terms of knowledge relatedness, design relatedness is a measurement of design quality. Thus, it can be found that exports can drive not only the number of designs registered overseas but also the quality of designs registered overseas.

4.6.2.3 Drivers of Exports

According to the IRF analysis, both the number of overseas design registrations and overseas design relatedness impact exports, and conversely, exports impact both. Based on the results of the Granger test, it can be found that both the number of overseas design registrations and overseas design relatedness have an interaction effect on exports. As it has been argued that design can drive exports from both the perspective of overseas intellectual property protection and knowledge relatedness. On the other hand, this phenomenon can also be explained as both overseas design quantity and quality can drive exports.

Overseas design quantity is measured by the number of designs registered in a foreign country for a given sector in a given year. This is a flow measure of design count. When it is shown to play a promoting role in the export flow, this can be explained from two perspectives: First, the increase in intellectual property protection in a foreign country can provide opportunities and reduce uncertainty for firms. Second, an increasing number of intellectual property rights registered in the overseas market is caused by firms' offshoring intentions in order to deeply involve in the global market.

In addition to the number of overseas design registrations, overseas design relatedness is illustrated to be another driving force of exports. As found in existing literature, knowledge relatedness is a key driver of economic growth as well as exports (Jun et al., 2020). Previous research has focused on export performance in the countries of intellectual property rights (IPR) owners, which measures the total innovation capability of a country or economy. This study focuses on the design relatedness generated in the target destination market of exports. Therefore, in addition to the promoting role of knowledge relatedness in exports, this study also discovers that the knowledge network, which is produced by the exports into the destination market, can improve exports.

Although it has been discussed that both the number of overseas design registrations and design relatedness are drivers of exports, according to the FEVD results, the impact of the number of overseas design relatedness is relatively small compared to the impact of overseas design registration. According to Kogler et al. (2013), knowledge relatedness is also a knowledge network that can lead to sustainable growth. Taking into consideration the finding that design registration has a larger effect than exports on the number of new design relatedness generation in the overseas market, it can be said that existing design knowledge relatedness is the origin of the new design registration, and the new design registration reversely affects exports. In addition, compared to directly affecting export growth, design relatedness seems to play a role by affecting new design registration.

4.7 Conclusion

The interdependencies of overseas design registration, overseas design relatedness, and exports have been examined using the Panel Vector Autoregression (PVAR) approach. In addition to analyzing the mutual impact through the Impulse Response Function (IRF) plot, the Granger causality test has been conducted to examine the causal relationship. Furthermore, the Forecast Error Variance Decomposition (FEVD) has been employed to compare the different driving forces of each variable. The conclusion is discussed in the following parts: (i) Interdependencies, (ii) Drivers of Overseas Design Registration, (iii) Drivers of Overseas Design Relatedness, (iv) Drivers of Exports, and (v) Summary of Conclusion.

This study has utilized the PVAR approach to examine the interdependencies of overseas design registration, overseas design relatedness, and exports. The IRF analysis confirms that all three variables have a significant impact on each other, and the Granger causality test suggests the presence of mutual causality among them. Thus, it can be concluded that there exist interdependencies and mutual causality between overseas design registration, overseas design relatedness, and exports. Additionally, this study has provided a comprehensive investigation of the driving forces behind each variable.

The analysis reveals that both overseas design relatedness and exports have a significant impact on changes in overseas design registration. The Granger causality test further confirms that both variables are causes of new design registration in the overseas market. However, overseas design relatedness exerts a stronger influence on overseas design registration compared to exports.

The IRF analysis demonstrates that both overseas design registration and exports have a significant impact on overseas design relatedness. The Granger causality test confirms that both variables are causes of overseas design relatedness. Specifically, overseas design registration plays a more substantial role in driving overseas design relatedness compared to exports.

The analysis identifies overseas design registration and overseas design relatedness as statistically significant drivers of exports through the IRF analysis. The Granger causality test confirms that both variables significantly impact exports and are causes of exports. The FEVD results also indicate that overseas design registration plays a more important role in promoting exports compared to overseas design relatedness.

In summary, this study empirically verifies the interdependencies among overseas design registration, overseas design relatedness, and exports using the UK regional quarterly panel and the PVAR approach. Both overseas design relatedness and exports are causes of each variable in this system. Moreover, overseas design relatedness emerges as the core driving force behind both overseas new design registration and exports. Specifically, exports play a crucial role in driving overseas design relatedness and overseas new design registration.

This study suggests that cross-border designs owned by UK firms or individuals significantly impact regional exports to the destination country where their designs are protected. Conversely, exports drive both the registration of cross-border designs and the generation of design knowledge networks in foreign markets. Therefore, the design knowledge network serves as the core driver for the sustainable growth of new design registration and exports in overseas markets. Importantly, this knowledge network is primarily driven by new design registration in overseas markets. This implies that while registering industrial designs in corresponding markets can be beneficial for expanding business or exporting goods to foreign markets, the production of cross-sector designs and the establishment of an intensive design knowledge network have a significant impact on exports, leading to the sustainable development of exporters in the destination market.

Chapter 5

Collaborate to Design

5.1 Introduction

Collaboration between participants is an opportunity to access external resources and knowledge. However, firms must take care to avoid the outflow of commercial knowledge (Oxley and Sampson, 2004). Mutual trust and face-to-face interaction between collaborators can result in improved collaboration productivity and lead to increased innovation performance (Wan et al., 2022).

Innovation typically involves a high level of tacit knowledge (Senker, 2008), and industrial design is no exception. Industrial design relies heavily on design expertise and the cooperation of relevant specialists. Industrial design plays an important role in services, production of goods, particularly in today's globalised market place (Bryson and Rusten, 2011). According to the Design Council (2022), design sectors generate £97 billion in Gross Value Added (GVA) in 2019.

It has been demonstrated in a large body of literature that face-to-face contact is the most effective approach for tacit knowledge sharing (Haldin–Herrgard, 2000; Holste and Fields, 2010; Jeck and Baláž, 2020; McCann, 2008; Parente et al., 2022; Qdah et al., 2018; Scherngell, 2021). This is further supported by findings that demonstrate that face-to-face communication can help collaborators to integrate multiple projects involved (Chiu, 2002). However, there is still lack of empirical evidence to support this notion. In view of this, this research provides the first evidence for the positive effect of face-to-face communication on design collaboration which was measured via air connectivity.

The different industries have different requirements for face-to-face frequency. As a result, the effect of air connectivity can vary from sector to sector. Nunn (2007) states that contract-intensive sectors involve more incomplete contracts than non-contract-intensive ones; therefore, contract intensity - which can be found in the works of Nunn (2007) - can be used as an indication of the level of dependence on face-to-face communication. Businesses operating in contract-intensive sectors must make plenty of incomplete contractual agreements in order to operate, hence why regular negotiations are necessary.

Specifically, the focus of this research is international Design collaboration. This research needs to take into account the complexities of design when measuring the importance of face-to-face communication. To measure these complexities, this research has constructed a variable called design complexity which is based on the economic complexity theory (Hidalgo and Hausmann, 2009) and its application in patent data Balland, Boschma et al., 2019). At the sectoral level, this variable can be used as a measure of the dependence level on face-to-face communication.

Further research has shown that the high-speed development of artificial intelligence and virtual communication can improve teamwork (Bassanino et al., 2014). There remain debates over the effect of virtual communication, which this study seeks to empirically investigate regarding its relation to face-to-face interaction. Some papers argue that virtual tools can replace face-to-face interaction (Tomé-Fernández et al., 2020), while others suggest that it is an irreplaceable approach to tacit knowledge sharing (Parente et al., 2022; Qdah et al., 2018).

Overall, the development of artificial intelligence and virtual communication have demonstrated their capability of improving teamwork and their presence in communication. Despite the continuing arguments, there remains no denying the importance of both face-to-face interaction and virtual tools. Therefore, it is essential that the relationship between the two media be further explored in order to gain a better understanding of the effects of each upon communication.

The objective of this research is to examine the link between face-to-face communication and international design collaboration. It will analyse the variation of face-to-face communication strategies employed in various sectors, while taking into consideration different requested or required contact frequencies. Furthermore, as artificial intelligence progresses and virtual tools become widely used for efficient communication, the impact of virtual communication on traditional face-to-face communication will be considered.

Examining the connection between face-to-face communication and international design collaboration, this paper utilises cross-country firm-level design records data from Questel Intellectual Property Database and air traffic data which is widely used to capture the air connectivity (Denstadli et al., 2013; Strengers, 2015) from OAG over the period 2013-2018. A measure of international design collaboration is then constructed with joint ownership of design records as the dependent variable. Cross-border face-to-face communication is approximated by air connectivity between countries, whilst controlling for bilateral trade data and regional trade agreements in the models which are estimated using OLS and Poisson Pseudo Maximum Likelihood (PPML) techniques. The complexity of designs is considered as a proxy for the dependence on face-to-face communication, based on economic complexity theory and applications to patent data. Additionally, an exploration of the sectoral aspect of face-to-face communication is done to assess the different frequencies of these contacts across various sectors. To conclude the study, the roles of virtual communication and face-to-face communication are compared so as to reflect upon the implications of artificial intelligence adoption on business activities.

Consider design complexity as a proxy for the degree of dependence on face-to-face communication, based on the economic complexity theory (Hidalgo and Hausmann, 2009) and its application in patent data (Balland, Boschma et al., 2019). Additionally, investigate the sectoral heterogeneity of face-to-face communication, as various sectors have different demands or frequencies for face-to-face contact. Also compare the roles of virtual communication and face-to-face communication to shed light on the growing global concern about the implications of artificial intelligence adoption on business activities.

The findings of the study suggest: (i) Face-to-face communication plays a promoting role in facilitating international design collaboration.(ii) The effect of air links tends to be larger in sectors with a higher level of dependence on face-to-face contact.(iii) There appears to be a complementary effect between air connectivity and virtual connectivity, suggesting that virtual communication enhances the effectiveness and productivity of face-to-face communication.

This paper is crafted into the following sections: The Hypothesis Development section proposes hypotheses and explains theories behind them, as well as their rationale;

The Data and Measures section outlines the data employed in this research, including its sources and defining of variables; The Methodology section includes the strategy for estimation and variables used in modeling; The Results section presents the results of the regression; The Discussion section links the results to existing literature and theories to discuss and analyse the findings; Finally, the Conclusion summarises the paper at the end.

5.2 Hypothesis Development

In the context of ongoing globalisation, collaboration is a necessary skill (Praharaj, 2019) for individuals and organisations who hope to extend their business. Knowledge collaboration relies on information sharing of creative ideas to generate value-added innovation (Cheng and Chang, 2020; Smirnova et al., 2018). Therefore, in the design and innovation collaboration process, successful knowledge exchange requires motivation from knowledge owners to share their know-how effectively (Desouza, 2003). The know-how is typically considered as tacit knowledge and requires extensive interaction for proper communication, ultimately yielding tangible outputs and desired results (Mendi, 2007).

Industrial design is a type of intellectual property that involves a great deal of tacit knowledge which is determined by the inventors' creativity and ingenuity. Such tacit knowledge is often challenging to explain, so patent offices are continuously exploring ways to get a clear description of it (Durack, 2004). Furthermore, the outputs of patenting usually create values for the owners of these firms.

According to Solomon and Soltes (2015), when making investment decisions investors are more likely to make well-informed trading decisions if they have direct meetings with the recipients of their investments. Similarly, when industrial design is involved in an investment decision, an extensive physical interaction between the respective firms is necessary.

From the perspective of designers, industrial design is a process of innovation and a form of patent which can protect the appearance features of goods from commercial exploitation (WIPO, 16/01/2023). Effective collaboration within the innovation process is vital given that it involves the diffusion of both internal and external knowledge sources (Un et al., 2010; West and Bogers, 2014). Moreover, the generation of effective industrial designs, that involve tacit knowledge diffusion, depends highly on the decision-making of the knowledge holder and the manner in which collaborators interact (Haldin–Herrgard, 2000; Song and Ma, 2022).

Design collaboration is an integral process that involves multiple designers and the sharing of tacit knowledge (Idi and Khaidzir, 2018). Tacit knowledge encompasses know-how that is uncodified and distinct from patent technology, which can lead to a greater risk of opportunistic behavior from sellers (Mendi, 2007). As such, close consideration should be taken when mediating collaborations between designers.

The core issue with sharing or transferring tacit knowledge is how to reduce uncertainty and reliability among co-workers. Several research papers have suggested that face-to-face interaction is an effective way to do so (Haldin–Herrgard, 2000; Holste and Fields, 2010; Jeck and Baláž, 2020; Maggioni and Uberti, 2009; McCann, 2008; Panahi et al., 2013; Parente et al., 2022; Qdah et al., 2018; Scherngell, 2021).

The face-to-face interaction has been extensively explored as a means of improving the exchange of knowledge, particularly in the fields of creativity and high technology. As pointed out by Saxenian (1996), in-person meetings can facilitate higher levels of trust between collaborators and an increased frequency of mutual citation between firms. From their recent paper, Atkin et al. (2022) support these findings by demonstrating the importance of establishing trust through frequent face-to-face interactions of exchanging knowledge. Cvitanovic et al. (2021) also provide evidence for the benefits of such interactions.

According to Hsieh et al. (2018), radical innovation is necessary for firms to improve their growth. It has been further argued that when collaborating with foreign collaborators, the novelty of innovation is increased. As such, firms may opt to look beyond their domestic markets and seek out foreign collaborators in order to stay competitive and continue to innovate.

Territorial boundaries between countries hinder international cooperation (Parreira et al., 2017). Even in the absence of physical borders, geographical distance remains a major obstacle to successful collaborations (Hoekman et al., 2010). International air traffic plays a crucial role in promoting countries' growth and development (Alderighi and Gaggero, 2017). It enables access to overseas resources and markets, fostering free-market activities without logistical boundaries (Button and Taylor, 2000). Numerous studies across disciplines confirm transportation's role in economic growth (Ahlfeldt et al., 2015; Banerjee et al., 2020; Canning and Fay, 1993; Cristea, 2017; Hu and Liu, 2010; Pradhan and Bagchi, 2013).

Innovation collaboration has become increasingly time-sensitive, with associated costs of working with co-authors or collaborators growing. To ensure productive communication, there is an ever-increasing demand for face-to-face interactions (McCann, 2008). Coscia et al. (2020) have suggested that business travel between different countries can improve knowledge sharing, driving cross-border investments and bilateral trade. Additionally, if the knowledge is related to technology, a live demonstration is often considered the most effective approach to disseminating information – and air travel serves as an effective way to facilitate this kind of knowledge diffusion (Hovhannisyan and Keller, 2015).

As air travel is the predominant way of travelling internationally, leveraging air traffic data can provide a comprehensive measure of the level and degree of connections between different countries, thus offering an effective proxy for face-to-face communication (Brueckner, 2003; Denstadli et al., 2013; J.-L. Lu and Peeta, 2009; Strengers, 2015). Accordingly, using air connectivity as a proxy for face-to-face communication, it is possible to propose a fundamental hypothesis.

H1: Air connectivity facilitates international collaborations in industrial designs.

The unassailable status of border-crossing physical gatherings is not at the same level of significance for several sectors. As globalisation develops, the categories of ’self-contained’ segments are gradually vanishing. However, the underlying complexity of every sector still persists. For those that are relatively more self-contained, the need for intercontinental partnerships and collaboration is less than other sections (Clague et al., 1999). Industries paying close attention to contracts are suspected to involve intricate goods and relationship-specific investments (Nunn, 2007). Reciprocally, the supplier may encounter a ”hold-up problem” which is predominantly determined by social preferences (Haruvy et al., 2019). Therefore, all parties need to communicate and interact in a responsible and time-efficient way to receive suitable benefits or recompenses.

The ”contract intensity” measure of industries identified by Nunn (2007) serves as a useful indicator of their reliance on relation-specific investments. Consequently, it can be posited that in contract-intensive sectors, air connectivity plays an even more important role in facilitating face-to-face interactions.

Moreover, design-complex sectors necessitate increased knowledge diffusion in relation to design expertise. In the pursuit of industrial designs, it is essential that know-how and tacit knowledge be disseminated among related collaborators; however, this knowledge often exists on an uncodified basis (Durack, 2004; Mendi, 2007). Sectoral analysis reveals that tacit knowledge transference occurs at a high rate within Information Communication, Technology (ICT) relevant sections (Qdah et al., 2018). These project-centered fields, such as ICT affiliated industries, industrial design and other associated research and development disciplines generate tacit knowledge through face-to-face communication and interaction (Gertler, 2003).

The different demands on face-to-face communication for various industries, as well as the effect of air connectivity, can vary significantly. The degree of such demand can be established by examining contract intensity and design complexity at an industrial level. In summary, the impact of air connectivity on face-to-face communication can be ascertained based on contract intensity and design complexity on an industry basis:

H2: If air connectivity facilitates international collaborations in industrial designs, the effect is likely to be larger in industries with a higher level of dependence on face-to-face communication.

The development of artificial intelligence has provided numerous opportunities for design work and remote collaboration to be achieved online. For example, building design can now be done remotely through computer-supported communication (Kolarevic et al., 2000). This has enabled designers to collaborate on projects with no physical boundaries, allowing much more efficient workflows and improved final product quality. In addition, Bailey, Gupta et al. (2020) suggest that online social connectedness can spur economic growth between two different countries, due in part to the ability of businesses in both countries to connect on a deeper level.

Despite the increasing availability of convenient virtual communication tools, the costs associated with knowledge transfer have been steadily mounting with an increased demand for face-to-face contact in knowledge collaborations (McCann, 2008). While artificial intelligence can contribute to the visual aspect of these interactions, there are also certain nuances that cannot be replicated through digitalisation (Haldin–Herrgard, 2000; Parente et al., 2022). As such, the true benefits of interpersonal communication remain in-tact despite the emergence of digital communication. It follows that virtual communication cannot completely replace the benefits of face-to-face communication, however it can supplement its effects.

According to Van-Bel et al. (2009), social connectedness is a primary indicator of the communication and relatedness level of people between two places. High levels of social connectedness indicate that there is a greater degree of communication between those countries, subsequently enhancing trust, reducing information asymmetry, and fostering collaboration through international trade and knowledge sharing (Bailey, Cao et al., 2018; Bailey, Gupta et al., 2020).

In this context, social connectedness is measured by the strength of the Facebook friendship network. It serves a similar role to transportation in terms of communicating between two countries, though with a digital or virtual perspective. This allows for transmission of messages beyond the scope of in-person contact.

H3: If air connectivity has a larger effect in design-complex sectors, this effect is larger for country pairs with stronger online social connectedness.

5.3 Data and Measures

5.3.1 International Design Collaboration

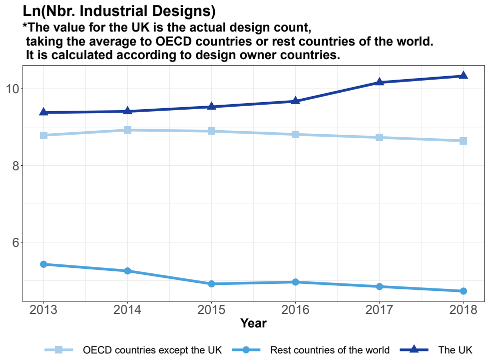
Design data is collected from Questel IP, providing raw records of design registration. The records contain detailed information such as the registration serial number, registration date, and registering/protecting countries or territories. Additionally, it includes owner information—name and address which is fundamental to generating a variable of international design collaboration.

Design collaboration is identified when at least two different owners can be detected in the same design record. This can be identified through its serial number of the design registration which acts as an identification number for each design record.

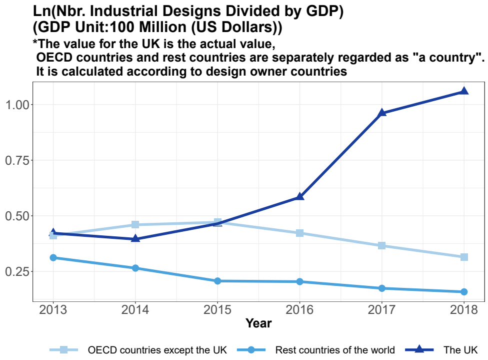
An international design collaboration is identified when collaborators (design owners) are from different countries. The count of international design collaborations for each combination of two different countries can be generated as the dependent varaible, moreover, this is computed on a yearly basis. The time coverage of this study is limited as 2013-2018.

Figure 5.1 presents a comparative analysis of design ownership in the United Kingdom, other Organisation for Economic Co-operation and Development (OECD) countries, and the rest of the world. To ensure a fair comparison, the number of designs is normalised by population and gross domestic product (GDP) for each country. Notably, the OECD countries are treated as a single entity, while the rest of the world is aggregated for ease of calculation and presentation within the figure.

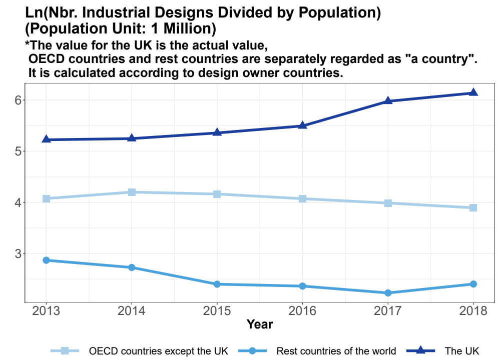
It is evident that the United Kingdom possesses a significantly larger number of designs compared to the average of other countries in the Organisation for Economic Co-operation and Development (OECD) as well as the rest of the world. Similarly, the average number of designs owned by each OECD country is also higher than the global average. When considering the ratio of designs to GDP, the UK exhibits a distinct upward trend, surpassing that of other OECD countries and the rest of the world. This



(a) Number of Design



(b) Number of Design Divided by GDP



(c) Number of Design Divided by Population

Figure 5.1: Comparison of UK, Other OECD countries, and The Rest of The World

suggests that the development of design in the UK is occurring at a rapid pace, outpacing the growth of its gross domestic product.

Furthermore, when examining the ratio of designs to population, the UK demonstrates a consistent increase between 2013 and 2018. In comparison to both OECD countries and the rest of the world, the UK maintains a higher value. This indicates that the rate of growth in registered designs owned by the UK exceeds the rate of population growth within the country. In contrast, other countries experience either lower rates or a balance between the increase in designs and population.

5.3.2 Air Connectivity

Air connectivity is approximated by air traffic data which is accessed from OAG. It is measured by the number of passengers flying from country i to country j, in year t, during the period of 2013-2018. In other words, air connectivity is also the intensity of air transportation between different countries. There are various ways to measure the number of passengers depending on certain factors such as cabin class, non-stop flights, and peak month in a given year. These metrics can be used as replaced when doing a robustness test.

5.3.3 Design Complexity

Design Complexity is a measure which can capture how design-specialised a USIO (1997) sector is, at the level of sector and year, still utilising the design rights records in the Orbit database. Industrial designs with a higher level of complexity often consist of numerous distinct categories of design specifications compared to the average.

Following Balland, Boschma et al. (2019), the method of generating variable design complexity is similar to the technological complexity index. Therefore, the design complexity is an abstract index measure that reflects the complexity level of designs.

Data utilised to generate the variable was sourced from Questel IP, spanning the time period of 2013-2018. The design counts were created at a country-class-year level, and did not involve design collaboration in the creation of design complexity. Instead, complexity was determined via sectoral count of industrial designs.

5.3.4 Contract Intensity

Contract intensity is employed to measure the importance of relationship-specific investment in various sectors, this is an alternative measure of design complexity to capture the sectoral dependence level on face-to-face communication.

According to Nunn (2007), contract intensity is measured by a weighted ratio of relationship-specific investments present in a given sector. The higher the weighted ratio, the greater the presence of incomplete contracts in that sector (USIO sector). Bolton and Dewatripont (2004) further demonstrate the importance of incomplete contracts when trying to analyse ownership and control rights. Rabin (2011) points out that people often interact to achieve social goals which Thaler (2015) refers to as ”conditional cooperators”. In terms of design collaboration, fields that involve more incomplete contracts than others are seen as having high levels of uncertainty in regard to contract negotiations.

The contract intensity data conducted by Nunn (2007) can be directly accessed through Harvard University’s website (2022). This indicator of contract intensity is measured at the sectoral level and remains time-invariant.

5.3.5 Other Controls

Total trade value between two countries and its accompanying regional trade agreement are commonly used as control variables. The trade data is collected from the United Nations Comtrade database, typically including both export and import values in order to generate a total trade value for both country i and country j within sector k in year t. It should be noted that the raw trade values are reported using HS codes and therefore need to be converted to USIO sectors first. The resulting total trade value can then reliably be considered a control of how close two countries are in terms of international business.

From a policy perspective, existing trade-related literature has made use of regional trade agreements to capture the relationship between two countries. The Mario Larch Regional Trade Agreements Database(Bayreuth, 2021) provides data at the country-country-year level which is insufficient to allow for sectoral variation.

5.4 Methodology

5.4.1 Baseline Estimation

The baseline estimation provides an initial analysis of the correlation between air connectivity and international design collaboration. This evaluation can serve as a starting point to better understand the implications of air travel on collaborative design projects in a global landscape.

$$DesignCollaboration_{ijk,t} = \beta_0 + \beta_1 AirLinks_{ijt} + X\Gamma + \theta_{ij} + \delta_t + \omega_k + \epsilon_{ijt} \quad (5.1)$$

In Equation (5.1), the subscripts i, j, and t represent the owner country, a co-owner country, and a year, respectively. The variable $DesignCollaboration_{ijk,t}$ is a measure of industrial design collaborations between countries i and j over time t.

$AirLinks_{ijt}$ is the measure of air links between countries i and j, represented by the log number of air passenger traffic between country i and country j at year t. In the baseline estimation, this measure includes the total number of air passengers, the number of passengers in business-class cabins, and the number of non-stop air passengers. To further explore potential connections, different measures of AirLinksijt are tested separately in the baseline estimation.

X is a vector of control variables that vary on both the country-country-year and country-country-sector-year levels. Examples of these variables include regional trade agreements, total trade value (measured at sectoral level), etc. Γ represents the coefficient matrix associated with this vector of control variables.

Besides the main explanatory variables and other controls, a baseline estimation is improved by adding basic fixed effects to the estimation equation. These fixed effects capture the fundamental, unobserved variables at different levels of country pairs, years, and sectors.

The relation between θ_{ij} and variations across country pairs may take several forms, including those relating to time-invariant qualities such as common language, geo-distance, or even colony history. To capture global changes over time, a fixed effect, δ_t, is employed to meet this purpose. Similarly, specific factors that might influence international design collaboration in different sectors, can be accounted for using the fixed effect ω_k. ϵ_{ijkt} is the error term.

When estimating by PPML, the variable $DesignCollaboration_{ijk,t}$ is the number of co-owned designs (here denoted as $Nbr.Design$); when estimated by OLS, it is the logarithm of that number (here denoted as Ln(Nbr.Design). Since the variable $DesignCollaboration_{ijk,t}$ has a large number of zero values, the transformation used for its logarithm is $ln(x + 1)$. For all variables whose values include many zeroes, taking their logarithm is equal to adopting the transformation $ln(x + 1)$ in this study.

In the baseline estimation, the expected value of β_1 is statistically positive and significant, which suggests that air connectivity has a positive effect on fostering international design collaboration.

5.4.2 Sectoral Dependence on Face-to-face communication

In terms of the collaboration in industrial designs, the dependence on face-to-face communication could vary across different sectors, while this can be captured by design complexity. Nonetheless, air connectivity cannot be captured at sectoral level. This is one of limitations of this measurement, it causes that the relationship of air connectivity and international design collaboration cannot be investigated directly at the sectoral level.

In order to determine the collective relationship between air connectivity and international design collaboration across the world, a particular investigation model was constructed. This model incorporates the interaction term on design complexity and air connectivity, as illustrated by Equation (5.2).

$$DesignCollaboration_{ijk,t} = \beta_0 + \beta_1 AirLinks_{ijt} + \beta_2 DC_{kt} + \beta_3 AirLinks_{ijt} \times DC_{kt} + X\Gamma + \theta_{ij} + \delta_t + \omega_k + \epsilon_{ijt} \tag{5.2}$$

The addition of air connectivity as a modulator to design complexity is expected to have a positive effect on international design collaborations. Complex industrial designs are most dependent on face-to-face communication, yielding a higher level of tacit knowledge, which would otherwise be unobtainable from any other forms of interaction.

The relationship between air transport and design complexity allows for more efficient exchanges of information between collaborators, reducing the barrier for collaborative success.

Industrial designs that are highly dependent on face-to-face communication entail greater tacit knowledge, and therefore, design complexity can become an obstacle to collaboration. Anticipating that the variable of design complexity carries a negative influence on international design collaborations, the interaction term of air connectivity and design complexity is projected to be positive since air transport ameliorates difficulties encountered during face-to-face communication.

5.4.3 Complementary Effect of Physical and Virtual Connectivity

Using regression, the sample used to evaluate the effect of air connectivity on international design collaborations across country pairs with different levels of social connectedness index can be split into 4 based on their quartile of the social connectedness index. To understand the impact of these connections, Poisson pseudo-maximum likelihood (PPML) can be used as a suitable estimation technique. The measurement for the total number of passengers between countries ($AirLinks_{ijt}$) will provide an indication of the level of air connectivity and its effect on international design collaboration activities. See Equation (5.3) for the model specification.

$$DesignCollaboration_{ijk,t} = \beta_0 + \beta_2 DC_{kt} + \beta_3 AirLinks_{ijt} \times DC_{kt} + X\Gamma + \zeta_{ijt} + \omega_k + \epsilon_{ijt} \tag{5.3}$$

When comparing quartile groups to one another, it is important to understand the significance of differences in estimates. To achieve this, the estimates and standard errors of β_3 are extracted and plotted in a line chart with a ribbon band. The ribbon band is derived by calculating the confidence interval for each group using the formula $\beta_3 \pm t \times se$, where t is the value at the 95% significance level. If there is no intersection between the confidence intervals of estimates when comparing quartile groups, it can be argued that there are significant differences across groups.

5.5 Results

The results section presents the estimation results produced by the methods proposed in the previous paragraphs. The structure of this section is the same as that of the methodology section.

The results of the basic model estimation and the tests of H1 were presented in the subsection of baseline results. The findings showed that air connectivity had a significant effect on various sectors.

In the subsection of sectoral heterogeneity, it was shown that the effect of air connectivity varied across sectors. This supports the hypothesis (H2) that the effects of air connectivity vary depending on the sector differences.

In the subsection of complementary effect between physical and virtual connectivity, it was observed that the effect of air connectivity changed with different levels of online social connectedness. This suggests that physical and virtual connectivity have a complementary effect, as previously proposed by the hypothesis (H3).

5.5.1 Baseline: Air Connectivity Drives International Design Collaboration

The baseline results discuss the effect of air connectivity on international design collaboration. The estimation work was carried out through two different estimators, OLS and PPML. The differences of air connectivity effect when measured by the total number of passengers, the number of non-stop passengers, and the number of business-class passengers are also discussed. Furthermore, the performance of control variables is mentioned.

As presented in Table 5.1, switching measures of air connectivity returns to the same results. By OLS estimator, the estimate of the total number of passengers is statistically significant and positive at the significance level of 0.001; while by PPML estimator, the estimate of the total number of passengers is also statistically significant and positive at the significance level of 0.05. It suggests that the air traffic can significantly and positively affect cross-border collaboration in industrial designs. As the air connectivity is measured by the total number of passengers, the estimation is not only an indicator to say if air connectivity can affect international design collaboration but also the reference to compare how the estimates fluctuate along with the change of measures of air connectivity.

Based on the results found in Table 5.1, international design collaboration is more sensitive to business-class air transport than to either the total number of passengers or the number of non-stop passengers. When air connectivity is measured by the number of business-class passengers, the coefficient is higher than when it is measured by the total number of passengers (by 52.94% using OLS and 181.61% using PPML), as well as by 477.78% with OLS and 326.62% with PPML when compared with estimates based on the number of non-stop passengers. These figures show that business-class transport proves to be a more important factor in facilitating international design collaboration.

However, compared to the other two measures (i.e. the total number of passengers and the business-class passengers), international design collaboration does not tend to be more sensitive to the number of non-stop passengers. Design collaborators value time cost while the general air transport is only a rough measure of passengers exchanged between countries; the number of non-stop passengers takes this into consideration.

Hypothesis Test of H1: Air connectivity facilitates international design collaboration						
Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML
Air Connectivity Measured by: Ln(Nbr. Passengers)	0.0034***	0.0609*				
	(0.0005)	(0.0260)				
Air Connectivity Measured by: Ln(Nbr. Non-stop Passengers)			0.0009***	0.0402***		
			(0.0001)	(0.0044)		
Air Connectivity Measured by: Ln(Nbr. Business-class Passengers)					0.0052***	0.1715***
					(0.0002)	(0.0157)
Total Trade Value	-0.0004***	0.0059	-0.0004***	0.0057	-0.0004***	0.0061
	(0.0001)	(0.0032)	(0.0001)	(0.0032)	(0.0001)	(0.0032)
RTA	0.0032***	0.3495***	0.0040***	0.4065***	0.0025***	0.3413***
	(0.0003)	(0.0673)	(0.0003)	(0.0638)	(0.0003)	(0.0639)
Constant	0.0017	-0.9988***	0.0326***	-0.6875***	-0.0048*	-1.8247***
	(0.0055)	(0.3000)	(0.0008)	(0.0722)	(0.0022)	(0.1537)
Fixed Effect	ij k t	ij k t	ij k t	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.3271		0.3271		0.3271	
Pseudo R-squared		0.6073		0.6075		0.6076
Log-likelihood	983701.5183	-227796.9292	983726.7282	-227680.8548	983795.1253	-227605.6755
Nbr.Obs	1870914	1870914	1870914	1870914	1870914	1870914

Table 5.1: Baseline Estimation

Nevertheless, the number of business-class passengers seems to include the time concern. From a commercial collaboration perspective, the business-class flight is more target specific.

It has been found that regional trade agreements are the only statistically significant variable in baseline estimation. This implies that these agreements can act as a driving force of international design collaboration, promoting mutual collaboration in industrial designs from the policy aspect. However, bilateral trade does not seem to indicate an influence on facilitating the design collaboration between two parties. This conclusion is evidenced by the contrasting results of total trade value in the baseline estimation, depending upon the method used for estimation. In OLS estimation, the estimates are significant and negative; while in PPML estimation, they are insignificant but positive.

5.5.2 Sectoral Dependence on Face-to-face communication

Estimation of sectoral heterogeneity focuses on how air connectivity differently affects international design collaboration in various sectors, due to the dependence level on face-to-face communication varying in different sectors. In this set of estimations, a variable, Design Complexity, is added to capture the face-to-face dependence level in terms of industrial designs, while the baseline variable, Air Connectivity, is used to see whether or not it can generally keep consistent with the baseline results. Moreover, the interaction term of Air Connectivity and Design Complexity in this section indicates to what extent the effect of air connectivity changes across different levels of design complexity.

Estimates of air connectivity remain positive and statistically significant, even when the variable of design complexity and interaction terms are added (see Table 7.5). Additionally, when air connectivity is measured by the number of business-class passengers, estimates can reach their highest values. The significance levels are identical to those of the baseline estimates, without any change in the difference percentages.

Moreover, according to Table 7.5, the design complexity is significantly and negatively correlated with the international design collaboration. This implies that a high level of design complexity brings about barriers to collaboration. In this case, collaborators need to communicate effectively in order to share or exchange tacit knowledge productively with each other. Furthermore, when air connectivity is measured by the number of non-stop passengers, absolute values of estimated coefficients of design complexity reach the minimum. Taking into consideration the negative effect, it can be concluded that non-stop flights reduce the barriers resulting from design complexity, which also indirectly facilitates design collaborations.

The estimate of the interaction term between air connectivity and design complexity remain statistically significant and positive regardless which estimator or measure of air connectivity is used. This suggests that air connectivity has an even stronger influence

Hypothesis Test of H2: Air Connectivity Has A Larger Effect in Sectors with Higher Dependence on Face-to-face Communication						
Air Connectivity Measured by:	Ln(Nbr. Passengers)	Ln(Nbr. Passengers)	Ln(Nbr. Non-stop Passengers)	Ln(Nbr. Non-stop Passengers)	Ln(Nbr. Business-class Passengers)	Ln(Nbr. Business-class Passengers)
Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML
Air Connectivity	0.0034***	0.0609*	0.0009***	0.0400***	0.0052***	0.1709***
	(0.0005)	(0.0261)	(0.0001)	(0.0044)	(0.0002)	(0.0156)
Design Complexity	-0.0040***	-0.1519***	-0.0013***	-0.0518***	-0.0031***	-0.0926***
	(0.0005)	(0.0212)	(0.0001)	(0.0098)	(0.0004)	(0.0174)
Air Connectivity x Design Complexity	0.0003***	0.0140***	0.0001***	0.0068***	0.0003***	0.0113***
	(0.0000)	(0.0019)	(0.0000)	(0.0010)	(0.0000)	(0.0019)
Total Trade Value	-0.0004***	0.0059	-0.0004***	0.0057	-0.0004***	0.0060
	(0.0001)	(0.0032)	(0.0001)	(0.0032)	(0.0001)	(0.0032)
RTA	0.0032***	0.3495***	0.0040***	0.4054***	0.0025***	0.3414***
	(0.0003)	(0.0673)	(0.0003)	(0.0638)	(0.0003)	(0.0639)
Constant	0.0017	-0.9988***	0.0326***	-0.6869***	-0.0048*	-1.8186***
	(0.0056)	(0.3015)	(0.0008)	(0.0721)	(0.0022)	(0.1534)
Fixed Effect	ij k t	ij k t	ij k t	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.3271		0.3271		0.3271	
Pseudo R-squared		0.6075		0.6076		0.6077
Log-likelihood	983733.4180	-227707.7270	983753.4134	-227601.3297	983826.9073	-227547.4695
Nbr.Obs	1870914	1870914	1870914	1870914	1870914	1870914

Table 5.2: Sectoral Heterogeneity

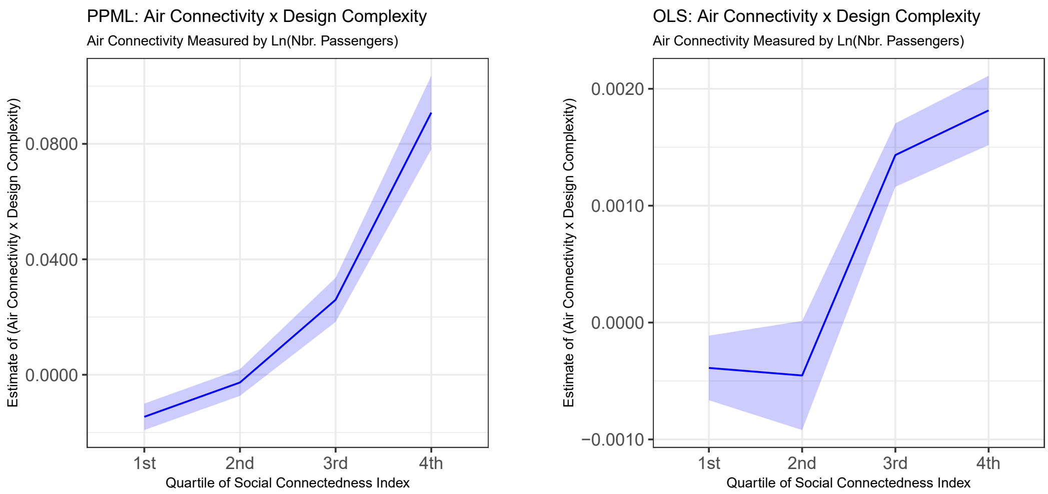
in sectors with high design complexity. As previously mentioned, design complexity is an indicator of how much face-to-face communication specific sectors depend on and thus, it is safe to say that in such industries, air connectivity plays a more crucial role.

In addition, the estimates of control variables are identical to those in the baseline estimation. Regional trade agreements can be empirically proven to play a significant role in improving international design collaboration; however, total trade value does not appear to significantly affect design collaborations between bilateral countries.

5.5.3 Complementary Effect of Physical and Virtual Connectivity

The physical connectivity as well as the air transport has a positive role in facilitating cross-border collaborations in industrial designs. It has been demonstrated that this physical connectivity has a larger effect in sectors with higher levels of design complexity. This section further investigates the relationship between physical and virtual connectivity, examining their complementary effects in different levels of online social connectedness by measuring the interaction term between air connectivity and the design complexity.

Figure (5.2) illustrates the increasing effect of air connectivity across online social connectedness. The y-axis in this figure represents the estimated interaction between air connectivity and design complexity, with the four points on the x-axis representing the four quantiles of the data sample. The shadow ribbon indicates the possible values of the estimates at the 95% confidence interval.



(a) Estimated by PPML

(b) Estimated by OLS

Figure 5.2: Complementary effect of physical connctivity and virtual connectivity

As it is presented in figure 5.2b, results obtained from Ordinary Least Squares (OLS) estimation show that coefficients of $AirLinks_{ijt} \times DC_{kt}$ increase along with the quartiles. The confidence interval of estimates in the fourth quartile does not intersect with the first quartile, indicating a significantly significant increase in the estimates when online social connectedness index shifts from the lowest level to the highest level.

The same results are presented in figure 5.2a from Poisson Pseudo Maximum Likelihood (PPML) estimation.

The importance of air connectivity in sectors that require a greater amount of direct human interaction is clearly illustrated. As shown by Figure 5.2 increased online social connectedness can lead to an even more important role for air connectivity in such sectors. This suggests that air connectivity can not only be beneficial in facilitating face-to-face contact, but additionally be encouraged through virtual connectivity between different country pairs.

5.6 Robustness Test

The robustness test is divided into four subsections: (i). The effect of air connectivity on international design collaboration can be tested again by replacing measures of air connectivity in baseline estimation with the corresponding passenger volume in the peak month of the year. This robustness test serves to support Hypothesis 1. (ii). To test H2, alternative measures (contract intensity) of the dependence level on face-to-face communication can replace the design complexity, and provide robustness results in terms of sectoral heterogeneity. (iii). The set of fixed effects can be enhanced to capture unobserved country-country-year-specific factors and optimise the model specification in the estimation of H2 (sectoral heterogeneity). However, this test cannot be directly applied to the baseline estimation since the key explanatory variable (air connectivity) is also country-country-year-specific. (iv). The robustness test of the complementary effect between air connectivity and virtual connectivity is a separate section, which would involve alternative measures of both air connectivity and design complexity, this serves to H3.

5.6.1 Alternative Measures of Air Connectivity

When attempting to measure air connectivity, endogeneity can be an issue if the annual amount of passengers is used as the measurement. This is because the passenger amount in a year can be mutually affected by the bilateral collaboration of countries. Replacing the passenger amount with the airline's capacity can effectively reduce this issue. The airline capacity can be approximated by the number of passengers in the peak month, making the measurement more exogenous than the annual passenger volume.

Therefore, in the robustness test of baseline estimation, the number of passengers in year t could be replaced by the number of passengers in the peak month of year t; the number of non-stop passengers in year t would be replaced by the number of non-stop passengers in the peak month of year t; the number of business-class passengers in year t would be replaced by the number of business-class passengers in the peak month of year t. To some extent, the limitation of this measurement is that the number of passengers in the peak month cannot perfectly represent yearly amount of passengers.

As presented in Table 5.3, it can be observed that following the adoption of an alternative measure of air connectivity, the baseline robustness test result remained consistent with the initial benchmark estimation. These results are statistically significant and positive in nature.

However, the sensitivity of international design collaboration on business-class air

Robustness Test	H1	H1	H1	H1	H1	H1
Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML
Air Connectivity Measured by: Ln(Nbr. Passengers in Peak Month)	0.0040***	0.0763**				
	(0.0005)	(0.0236)				
Air Connectivity Measured by: Ln(Nbr. Non-stop Passengers in Peak Month)			0.0011***	0.0462***		
			(0.0001)	(0.0053)		
Air Connectivity Measured by: Ln(Nbr. Business-class Passengers in Peak Month)					0.0011**	0.0431
					(0.0004)	(0.0267)
Total Trade Value	-0.0004***	0.0059	-0.0004***	0.0057	-0.0004***	0.0061
	(0.0001)	(0.0032)	(0.0001)	(0.0032)	(0.0001)	(0.0032)
RTA	0.0031***	0.3495***	0.0040***	0.4063***	0.0031***	0.3507***
	(0.0003)	(0.0673)	(0.0003)	(0.0640)	(0.0003)	(0.0669)
Constant	0.0015	-1.0537***	0.0324***	-0.6802***	0.0308***	-0.6733**
	(0.0046)	(0.2373)	(0.0008)	(0.0730)	(0.0031)	(0.2404)
Fixed Effect	ij k t	ij k t	ij k t	ij k t	ij k t	ij k t
Cluster	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.3271		0.3271		0.3270	
Pseudo R-squared		0.6073		0.6075		0.6073
Log-likelihood	983706.0523	-227792.4506	983729.9585	-227676.6797	983687.3784	-227801.3249
Nbr.Obs	1870914	1870914	1870914	1870914	1870914	1870914

Table 5.3: Robustness Test: Air Connectivity Drives International Design Collaboration

transport cannot pass the robustness test. If alternative measures of air connectivity are adopted in estimation, business-class transport is not likely to play an important role in facilitating international design collaboration, due to the estimates of air connectivity measured by business-class passengers not tending to be larger than those measured by total passenger amount or the number of non-stop passengers.

5.6.2 Alternative Measures of Sectoral Face-to-face Dependence

To capture the impact of air connectivity on international design collaboration in various sectors, two key measures are used - design complexity and contract intensity. Design complexity is a measure that captures the dependence level of face-to-face communication, while contract intensity is a measure to understand the importance of face-to-face communication. To further verify sectoral heterogeneity, contract intensity can be used as an alternate measure instead of design complexity. However, contract intensity would be omitted from the regression model due to its collinearity with the sectoral fixed effect. The estimates of the interaction term of air connectivity and contract intensity is the focus of the robustness test for measuring sectoral heterogeneity.

The robustness test, shown in Table 5.4, compared the performance of contract intensity as an alternative measure for design complexity. This method offers a sector-specific view at the same time being time-invariant; however, it also comes with a limitation. Specifically, since the sample used is a panel, it may introduce bias in the estimation process.

It can be observed from Table 5.4 that the interaction term of air connectivity and contract intensity remains positive and significant, suggesting that air connectivity can help promote international design collaboration more productively in sectors where face-to-face communication relies heavily. Even when the corresponding variable changes, the estimated interaction between air connectivity and contract intensity appears to remain intact.

5.6.3 Model Specification

When estimating the sectoral heterogeneity, the model specification includes the fixed effects which capture country-pair-specific, sectoral and time-variant factors. However, if there are unobserved variables at country-country-time level, this set of fixed effects cannot capture them. Furthermore, if the country-country-time fixed effect is included, air connectivity would be omitted due to collinearity. Therefore, in order to investigate the role of air connectivity in international design collaboration, the country-country-time-specific fixed effect must not be included in the model specification.

Since the estimates of air connectivity have been clearly presented in previous estimation, it is necessary to take a stronger fixed effect into consideration in order to determine if the interaction between air connectivity and the dependence on face-to-face communication can still yield a positive and significant role as before.

Robustness Test	H2	H2	H2	H2	H2	H2
Air Connectivity Measured by:	Ln(Nbr. Passengers)	Ln(Nbr. Passengers)	Ln(Nbr. Non-stop Passengers)	Ln(Nbr. Non-stop Passengers)	Ln(Nbr. Business-class Passengers)	Ln(Nbr. Business-class Passengers)
Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML
Air Connectivity	0.0014**	0.0172	0.0001	0.0266***	0.0028***	0.1212***
	(0.0005)	(0.0264)	(0.0001)	(0.0062)	(0.0003)	(0.0147)
Air Connectivity x Contract Intensity	0.0038***	0.0758***	0.0016***	0.0232*	0.0046***	0.0865***
	(0.0005)	(0.0178)	(0.0002)	(0.0090)	(0.0005)	(0.0171)
Total Trade Value	-0.0004***	0.0061	-0.0003***	0.0058	-0.0004***	0.0063*
	(0.0001)	(0.0032)	(0.0001)	(0.0032)	(0.0001)	(0.0032)
RTA	0.0032***	0.3494***	0.0040***	0.4065***	0.0025***	0.3411***
	(0.0003)	(0.0673)	(0.0003)	(0.0638)	(0.0003)	(0.0638)
Constant	0.0014	-1.0144***	0.0321***	-0.6901***	-0.0052*	-1.8361***
	(0.0055)	(0.3015)	(0.0008)	(0.0728)	(0.0022)	(0.1546)
Fixed Effect	ij t k	ij t k	ij t k	ij t k	ij t k	ij t k
Cluster	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.3272		0.3272		0.3273	
Pseudo R-squared		0.6076		0.6076		0.6080
Log-likelihood	983900.0402	-227642.3539	983915.6899	-227626.2497	984092.9455	-227406.9409
Nbr.Obs	1870914	1870914	1870914	1870914	1870914	1870914

Table 5.4: Robustness Test of H2: Alternative Measure of Sectoral Dependence on Face-to-face Communication

Robustness Test	H2	H2	H2	H2	H2	H2
Air Connectivity Measured by:	Ln(Nbr. Passengers)	Ln(Nbr. Passengers)	Ln(Nbr. Non-stop Passengers)	Ln(Nbr. Non-stop Passengers)	Ln(Nbr. Business-class Passengers)	Ln(Nbr. Business-class Passengers)
Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML
Design Complexity	-0.0077***	-0.1627***	-0.0034***	-0.0558***	-0.0064***	-0.1045***
	(0.0010)	(0.0201)	(0.0003)	(0.0088)	(0.0008)	(0.0165)
Air Connectivity x Design Complexity	0.0006***	0.0150***	0.0003***	0.0073***	0.0006***	0.0126***
	(0.0001)	(0.0018)	(0.0000)	(0.0010)	(0.0001)	(0.0018)
Total Trade Value	0.0000	0.0116***	0.0000	0.0117***	0.0000	0.0116***
	(0.0001)	(0.0035)	(0.0001)	(0.0035)	(0.0001)	(0.0035)
Constant	0.0892***	0.1554**	0.0891***	0.1542**	0.0892***	0.1563**
	(0.0015)	(0.0503)	(0.0015)	(0.0506)	(0.0015)	(0.0504)
Fixed Effect	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k
Cluster	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.4538		0.4538		0.4538	
Pseudo R-squared		0.6028		0.6028		0.6027
Log-likelihood	179167.4005	-184207.9894	179167.8437	-184218.9214	179168.4537	-184236.3587
Nbr.Obs	784356	784356	784356	784356	784356	784356

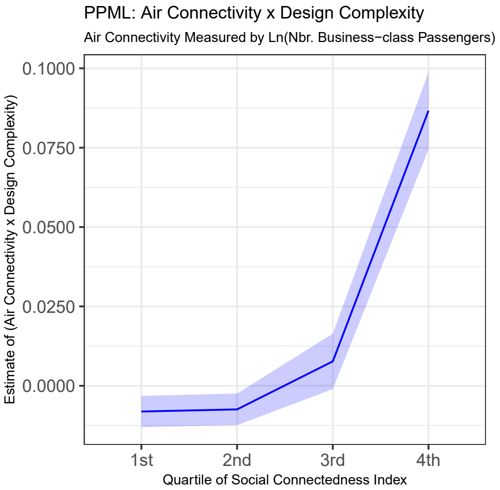
Table 5.5: Robustness Test of H2: Altrnative Fixed Effects

As shown in Table 5.5, the fixed effect (*ijt*) has replaced the separate fixed effects (*ij* and *t*). The estimates of the interaction between air connectivity and design complexity remain positive and significant, with only minimal changes in their values. This suggests that Hypothesis 2 passes the robustness test, confirming that air connectivity can have a larger positive effect on sectors where face-to-face communication is more prominent.

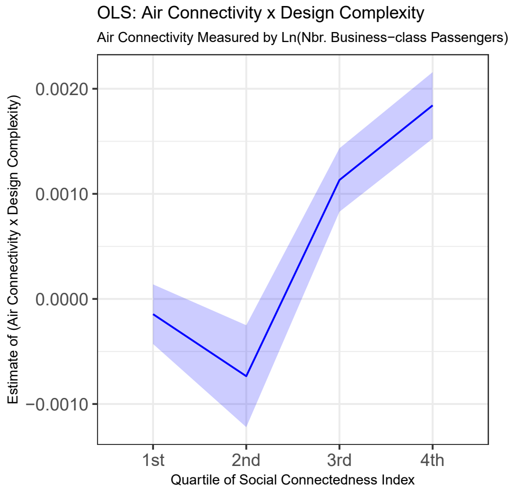
5.6.4 Complementary Effect of Physical and Virtual Connectivity

In the robustness test of the complementary effect of physical and virtual connectivity, the total number of passengers would be replaced by the number of business-class passengers, since the international design collaboration is considered to be more sensitive to business-class flights. Besides, fixing the measure of air connectivity as the total number of passengers, the product complexity or manufacturing complexity can be replaced by contract intensity in Equation (5.3).

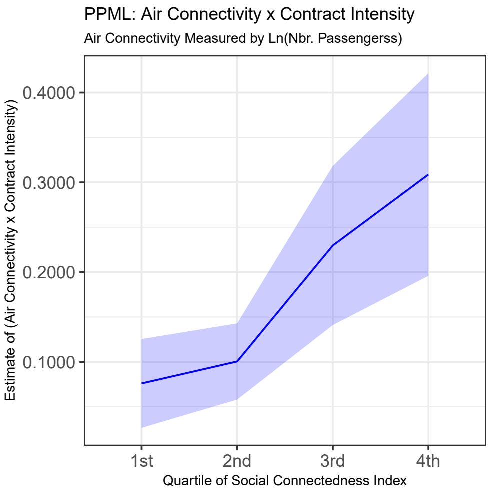
It can be seen from Figure 5.3 that substituting existing variables with alternatives of air connectivity and design complexity does not affect the overall results. The results are consistent with the original estimation.



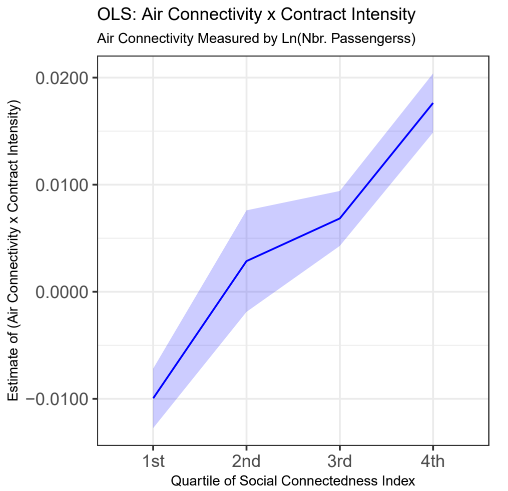
(a) Estimated by PPML



(b) Estimated by OLS



(c) Estimated by PPML



(d) Estimated by OLS

Figure 5.3: Robustness Test: Complementary Effect

5.7 Discussion

5.7.1 Air Connectivity Drives International Design Collaboration

Combining the results of the robustness test to H1, when measuring air connectivity by the total number of passengers, it can be concluded that the baseline estimation and the robustness test point to statistically significant and positive estimates of air connectivity. Therefore, the empirical evidence supports the argument that air connectivity does have a positive effect on international design collaboration. Furthermore, the robustness test suggests that when the total number of passengers is replaced with passenger volume during the peak month, the estimates for air connectivity are higher and more significant.

This research is providing an empirical evidence of the promoting effect of air transportation on international design collaboration. This evidence complements existing literature about knowledge collaboration, as previously proposed by Ploszaj et al. (2020) that a sufficient capacity of the air transport system is required for international research collaboration. From the point of view of industrial designs, the findings suggest that air transport is one of the main drivers of successful international design collaboration. Thus, this evidence contributes to the current understanding of knowledge collaboration.

Moreover, the findings can contribute to research on face-to-face communication, since air connectivity aims to capture the frequency of face-to-face communication between different countries. It can be argued that face-to-face contact facilitates international design collaboration, which is also supported by other research. While face-to-face communication is considered to play a pivotal role in tacit knowledge diffusion–a crucial part of knowledge exchange (Pérez-Luño et al., 2019)–its effect on knowledge exchange can be discussed in light of existing literature. For example, according to Tan (2016), there is a positive relationship between face-to-face communication and knowledge exchange.

In brief, the positive effects of air connectivity and face-to-face communication on international design collaboration can be demonstrated through both results and robustness tests. This finding is further attested by existing literature (Pérez-Luño et al., 2019; Ploszaj et al., 2020; Tan, 2016) which have explored the effect of face-to-face contact on knowledge sharing or economic activities.

5.7.2 Sectoral Dependence on Face-to-face Communication

There is sufficient evidence presented in the results and robustness test sections to illustrate that air connectivity has a larger effect in sectors with a high dependency on face-to-face communication. The estimation of coefficients for the interaction term of air connectivity and face-to-face dependence remain positive and significant in both fundamental estimations and robustness tests. This is further expounded on by existing research demonstrating an increase in innovation productivity by having frequent face-to-face meetings in knowledge-intensive sectors (**Wiig.2007**).

The study of design complexity can be of much relevance to different research areas, such as the application of technological complexity theory (Balland, Boschma et al., 2019) and the measurement of dependence on in-person communication in the industrial design field. As a consequence of technological complexity, design complexity is considered to be a barrier to international design collaboration.

Technological complexity is known to play a key role in economic growth (Mewes and Broekel, 2022); however, the complexities of design can have a detrimental effect on design collaboration. This research examines how to reduce the barriers caused by design complexity, proposing a possible solution.

Findings in this study suggest that adequate air transport can alleviate the negative impact of design complexity on collaboration. To this end, strategies such as improving air transportation and increasing the availability of air connectivity may be useful in mitigating the difficulties posed by design complexity. Additionally, furthering efforts in research and development, as well as enhancing educational programs related to design technology, may also facilitate successful and productive design collaborations.

Summarising, the research presented here provides initial empirical evidence of the difficulties international design collaboration may face when frequent face-to-face communication is necessary. Air transportation can help reduce these issues, as it has a larger promoting effect on sectors with a higher requirement for face-to-face contact.

5.7.3 Complementary Effect

Air connectivity tends to have a complementary effect with virtual connectivity. Compared to country pairs with the average level of online social connectedness, air connectivity appears to play a more important role in bilateral countries with a higher level of online social connectedness. As shown in the results section, air connectivity has a larger effect in sectors with a higher dependence level on face-to-face communication, this effect would be even greater for countries with a higher online social connectedness.

In existing research, virtual tools have been considered to help facilitate communication. This study provides the first evidence of a complementary effect resulting from physical and virtual connectivity with respect to design collaboration. Examples of this can be found in the construction industry, where practitioners emphasise the value of a virtual approach to design collaboration (Kolarevic et al., 2000). However, as demonstrated by the results of this study, no amount of virtual interaction can replace face-to-face communication.

When it comes to design collaboration, the process involves extensive knowledge-sharing and exchange; thus, making face-to-face interaction an irreplaceable part of the process. As the three-way interaction term is employed in estimation, it can be found that along with the increased dependence on face-to-face communication, the promoting effect of air connectivity is increased. For knowledge-intensive sectors, if air transport is regarded as a possible solution to improve international design collaboration, then virtual communication can be a complementary approach to enhance the efficiency of face-to-face interactions.

5.7.4 Limitation

The dependence of face-to-face communication on collaboration in industrial design can vary across different sectors, and this factor can be taken into account when measuring design complexity. However, air connectivity cannot be accurately measured at a sectoral level; this is a limitation of the method and prevents an intimate investigation of how air connectivity affects international design collaborations.

In the robustness test of baseline estimation, air connectivity is approximated with the number of passengers in the peak month. This measurement has a limitation in that the number of passengers in the peak month cannot perfectly represent yearly amount of passengers. For instance, if the distribution air traffic flows is left-skewed in a given year, the passenger volume in the peak month would overestimate the number of passengers this year; conversely, if the distribution is right-skewed, then the annual passenger amount is underestimated.

The variable contract intensity which is used in the robustness test is sector-specific and time-invariant. It cannot capture how the sectoral demand for face-to-face communication changes over time, moreover, it would be omitted if estimating Equation (5.2) because of its collinearity with the fixed effectω_k.

5.8 Conclusion

This research studies the impact of air connectivity on international design collaboration. To measure this, data from registered industrial designs was used as well as air traffic data as a proxy for face-to-face communication between collaborators in different countries. The results of OLS and PPML regression analysis indicate that air connectivity has a positive effect on international design collaboration, suggesting that face-to-face communication plays an important role in the cross-border collaboration in industrial designs. Furthermore, the results were robustness tested to add extra credibility.

Moreover, this paper illustrates that air connectivity is more highly emphasised in sectors which are dependent on it due to their varying demands for face-to-face communication. Additionally, even though artificial intelligence has become increasingly important over the years, the study further argues that the use of face-to-face contact still remains irreplaceable for international design collaboration.

As the world continues to evolve technologically, future research in the field of international design collaboration is likely to increasingly focus on virtual connectivity. While this study emphasises the positive impact of air connectivity on cross-border collaboration, advancements in virtual collaboration platforms and communication technologies are expected to reshape the landscape of collaborative work.

Virtual connectivity offers the potential to overcome geographical barriers and facilitate real-time interactions among collaborators from different countries. With the growing sophistication of virtual reality (VR) and augmented reality (AR) technologies, remote design teams can simulate face-to-face interactions, enhancing communication and collaboration.

In the future, further research may explore how virtual collaboration platforms, cloud-based tools, and tangible user interfaces impact design behavior and cross-border collaboration. By leveraging these technologies, organisations can enhance efficiency, reduce costs, and foster innovation in international design projects.

Chapter 6

Conclusion

6.1 Introduction

The primary objective of this study is to investigate the impact of industrial design within the knowledge economy. Industrial design is assessed based on global design registration records obtained through Questel IP, encompassing a comprehensive collection of historical registered designs across the globe. Utilising this extensive dataset, relevant variables are constructed to address distinct hypotheses in each chapter. The research is structured into four distinct stages. Chapter 2 endeavors to provide a comprehensive overview of the evolutionary trajectory of industrial design and the prevailing global pattern of design registration, employing advanced data visualisation techniques.

Chapter 3 delves into the direct and indirect effects of industrial design on export activities, aiming to ascertain the extent to which design plays a pivotal role in facilitating exports. Furthermore, Chapter 4 adopts a different perspective to investigate the intricate relationship between design and exports, recognising the existence of an interrelationship between the two constructs. This interdependency is meticulously examined through the employment of a PVAR approach. Lastly, Chapter 5 identifies the increasing significance of cross-border collaboration in the era of globalisation, particularly in the realm of international design collaboration. Air connectivity is identified as a critical driver that fosters and encourages such collaborative efforts. The subsequent discourse in Chapter 5 delves into the profound implications of air connectivity in facilitating international design collaboration.

6.2 Global Pattern of Industrial Design Registration

Utilising the complete historical records of design registration, we present a comprehensive timeline depicting the evolution of industrial design. Notably, industrial design experienced rapid development during the onset of the third industrial revolution, with a substantial surge observed during the fourth industrial revolution. Remarkably, nearly 80% of global historical design registrations occurred during the Industry 4.0 era.

Moreover, our data visualisation analysis reveals a dominant ownership structure in the realm of industrial design as an intellectual property. A minority of countries, including prominent Asian nations such as South Korea and China, alongside European counterparts like France and Germany, possess the majority of industrial design rights. Consequently, it can be inferred that Asian and European countries exert significant control over the ownership of industrial design.

Furthermore, our data visualisation analysis uncovers an uneven distribution of industrial design across various design types. While certain countries dominate the industrial design landscape, design registrations exhibit intensity across all types within these dominant nations. Consequently, the global landscape of industrial design registration is shaped by the economies and countries involved, rather than specific design objectives.

Considering the potential for cross-border registration of industrial design, it becomes evident that the countries of origin may differ from the protection territories. Accordingly, our data visualisation analysis offers insights into the destination markets for industrial design registration, shedding light on the global pattern. Notably, we observe a significant concentration of design registrations in certain popular destination markets, driven by the imperative of protection. Historical records indicate that China stands as the most sought-after destination market globally, closely followed by European countries. Notably, European countries are often perceived as a unified market, attracting both European and non-European design holders seeking to register their industrial designs.

Moreover, the investigation into the destination market of industrial design reveals the prominence of cross-border design registration. Over time, it can be observed an increasing trend in cross-border design registrations, surpassing national cross-border registrations, particularly in recent years. Notably, European cross-border design registration exhibits exceptional prominence, underscoring the region's dual role as a dominant owner and popular destination market for cross-border design registrations.

Policy makers should prioritize enhancing transparency and accessibility of historical records of design registration to benefit researchers, innovators, and entrepreneurs by establishing online databases or platforms. They should also develop policies to promote innovation and collaboration in industrial design, focusing on emerging technologies and encouraging international partnerships. Additionally, addressing ownership disparities in industrial design rights is crucial, necessitating measures such as international agreements and capacity-building programs to ensure equitable distribution and access to intellectual property rights. Supporting diversity in design through initiatives that encourage exploration of various design types and styles can enrich the global design landscape. Moreover, policy makers should facilitate cross-border registration processes for industrial design by establishing frameworks for harmonizing registration systems and enhancing international cooperation. Strengthening intellectual property protection mechanisms globally, including providing technical assistance and training programs, is essential to safeguard industrial design rights.

6.3 Design as A Driver of Exports

Chapter 3 explores the pivotal role played by industrial design in facilitating the export of goods, particularly within the realm of innovation. The relationship between industrial design and exports is rigorously investigated through the utilisation of the Poisson Pseudo-Maximum Likelihood (PPML) estimation technique, employing data derived from design registration records and export values. Multiple design variables are meticulously formulated to address distinct hypotheses.

To ascertain the direct impact of industrial design on exports, variables encompassing design capability, design comparative advantage, design relatedness, and design relatedness density are constructed. The PPML estimation results substantiate the direct and instrumental role played by industrial design in promoting exports within exporting countries.

Furthermore, the indirect effect of industrial design on exports is examined by employing PPML regression models augmented with interaction terms. Specifically, the influence of design similarity and design complexity is scrutinised. Design similarity emerges as a salient moderator, tempering the direct effects of design relatedness and design capability on exports. Notably, heightened design similarity diminishes the positive impact of design relatedness and design capability on exports.

Similarly, the influence of design complexity on the direct effects of export similarity and design comparative advantage on exports is observed. Empirical findings reveal that exported commodities exhibiting elevated design complexity tend to yield a more pronounced and favourable effect on exports in terms of design comparative advantage. Furthermore, the adverse impact of export similarity on exports becomes more pronounced when exporting highly intricate commodities.

In summary, this chapter provides a comprehensive examination of the multifaceted role of industrial design in promoting exports. The analysis distinguishes between two distinct categories: the direct effect and the indirect effect on exports. The direct effect analysis underscores the positive influence exerted by design capability, design comparative advantage, and design relatedness within exporting countries. Conversely, the indirect effect analysis highlights the moderating role of design similarity in the relationship between design capability, design relatedness, and exports. Moreover, design complexity amplifies both the positive impact of design comparative advantage and the negative impact of export similarity on exports.

Investment in industrial design policies can significantly impact enterprise performance, including value added, competitiveness, and business growth. The effect of bureaucrats on exports is particularly notable in products with increasing import demand, indicating the importance of administrative capacity in implementing industrial policies effectively. Additionally, there's a policy implication that suggests the modification of intellectual property rights rules to better support industrial design. Understanding the position of craft within export sectors and navigating challenges such as Brexit are crucial for leveraging design and craft for export as part of modern industrial strategies. Engaging in both research and development (R&D) and design is strongly associated with exporting, highlighting the significance of innovation in driving export success in the creative industry.

6.4 Interdependencies of Design and Exports

The investigation into the motivation behind the registration of industrial designs from the perspective of intellectual property protection, specifically in relation to exporting intentions, is explored in Chapter PVAR. The interplay between industrial design registration and exports is hypothesised to exist due to the promoting role of industrial design in exports. Consequently, the subsequent chapter employs PVAR modelling to examine these interdependencies.

Utilising data on design records collected from Questel IP, design variables are derived from both the perspectives of overseas design capability and overseas design relatedness. Another variable of interest is the regional export value of the United Kingdom (UK). The study focuses on UK regions, which are considered both as owners of industrial design and as regions engaged in exporting. The analysis is limited to the time period between 2013 and 2019, encompassing a total of 28 quarters. These three variables serve as dependent variables in the PVAR model to explore their interdependencies.

The PVAR approach confirms the interrelationship among overseas design capability, overseas design relatedness, and exports. These factors mutually interact with one another. The existing overseas design capability of a region is identified as a driver for the generation of new design relatedness and future exports. Similarly, existing overseas design relatedness encourages the generation of new overseas design registrations and subsequent exports. As anticipated, regional exports contribute to the promotion of overseas design registration and the generation of design relatedness.

In summary, utilising the aforementioned variables, the analysis identifies a promoting effect of each variable on the others. Further comparison of the effects from different variables on a given variable is conducted using the Forecast Error Variance Decomposition (FEVD) technique. It is concluded that, for new overseas design registrations, existing overseas design relatedness exerts a greater effect than exports. However, for the generation of overseas design relatedness, existing exports play a more significant role than the existing number of design registrations in overseas markets. Additionally, the FEVD analysis suggests that exports are positively influenced by past overseas design relatedness to a greater extent than by the past number of overseas design registrations.

In summary, this chapter utilises the PVAR methodology to explore the interdependencies among overseas design registration, overseas design relatedness, and exports, with a specific focus on UK regions. The findings can be summarised in two aspects. Firstly, the interdependencies among the three variables are confirmed. Secondly, the effects of different variables on a given variable differ. Specifically, compared to exports, existing overseas design relatedness plays a more significant role in promoting new design registrations in foreign markets. Moreover, the generation of new design relatedness in foreign markets is more encouraged by exports than by the existing number of design registrations. Furthermore, exports are positively affected by overseas design relatedness to a greater extent than by the existing number of overseas design registrations.

The analysis using the PVAR methodology suggests several key policy implications for policymakers. Firstly, there's a need to enhance intellectual property protection, especially for industrial designs, recognizing their role in promoting exports [3]. Secondly, supporting overseas design capability through investment in initiatives is crucial, as it drives new design relatedness and future exports [6]. Thirdly, facilitating export promotion programs targeted at regions with existing overseas design relatedness can stimulate new design registrations in foreign markets [6]. Moreover, encouraging collaboration and knowledge exchange between exporting regions and those with design capability can foster innovation and design-related activities [6]. Lastly, investing in export-driven policies that leverage past overseas design relatedness to enhance exports is vital for fostering a conducive environment for export growth and innovation within the industrial design sector, particularly in the context of UK regions.

6.5 Air Connectivity Facilitates International Design Collaboration

The increasing international collaboration across various aspects of the global economy necessitates cross-border collaboration in the field of industrial design. Concurrently, global air connectivity, as a critical mode of transportation facilitating communication between individuals from different countries, is considered a pivotal factor in promoting international design collaboration. To investigate the extent to which global air connectivity can enhance international design collaboration, the final empirical research is conducted.

By utilising data on international design collaboration and the number of air passengers at the country-country-year level, this chapter aims to elucidate the role of air connectivity in driving the growth of international design collaboration. Through the employment of Poisson Pseudo-Maximum Likelihood (PPML) estimation, it is observed that air connectivity tends to facilitate international design collaboration. However, given the varying frequencies of face-to-face communication across different sectors, an investigation is further conducted to explore the differential impact of air connectivity in sectors with distinct face-to-face communication requirements.

Based on the PPML estimation incorporating the interaction term between contract intensity or design complexity and air connectivity, it is evident that air connectivity exerts a more pronounced effect in sectors with higher face-to-face communication requirements. Contract intensity serves as an alternative variable to capture the diverse frequencies across various sectors. The results are robust across both the baseline estimation and the subsequent robustness tests, thereby reinforcing the validity of this conclusion.

Furthermore, as air connectivity represents a measure of physical connectivity, it is regarded as a facilitator of international design collaboration in a physical sense. However, considering the increasing trend of online communication on a global scale, it is essential to investigate the interaction between air connectivity and online connectivity. By employing online social connectedness as a proxy for online connectivity, the interaction between online social connectedness and air connectivity is examined through PPML estimation. In conclusion, online connectivity plays a complementary role in facilitating international design collaboration, as the effect of air connectivity strengthens with increasing levels of online connectivity.

In summary, this chapter seeks to explore the role of air connectivity in promoting international design collaboration. In essence, air connectivity is identified as a driver of international design collaboration. Furthermore, the impact of air connectivity on international design collaboration is more pronounced in sectors characterised by a higher frequency of face-to-face communication. Moreover, online connectivity does not supplant face-to-face communication but rather complements the positive effect of air connectivity on international design collaboration.

This chapter emphasises the pivotal role of global air connectivity in fostering cross-border collaboration within industrial design and suggests several policy implications for policymakers. These include prioritising investment in air transport infrastructure to bolster international communication, encouraging cross-sector collaboration to accommodate varying communication needs across industries, integrating online connectivity with air transport initiatives to further enhance collaboration, allocating resources for research on the interaction between air and online connectivity, and fostering international collaboration initiatives to leverage air connectivity for knowledge exchange. These policies aim to leverage air connectivity to drive international collaboration in industrial design while acknowledging the evolving landscape of communication in the global economy, encompassing both physical and virtual realms.

6.6 Summary of Conclusion

The conclusion chapter of this study focuses on exploring the role of industrial design in the knowledge economy, specifically considering it as intangible assets. The research utilises data from design registration records worldwide, collected through Questel IP.

The global pattern of industrial design registration is examined using data visualisation. It is found that industrial design is dominated by a few owner countries, mainly in Asia (such as South Korea and China) and Europe (including France and Germany). The distribution pattern of industrial design is determined by countries/economies rather than design objectives. Popular destination markets for design registration are China and European countries, which are attractive to both European and non-European design holders. Cross-border design registration, especially in Europe, is increasing significantly.

The role of industrial design in exports is explored, considering its promotion of goods exports as part of innovation. Design capability, design comparative advantage, and design relatedness in exporting countries are found to have a positive direct effect on exports. Design similarity and complexity also have indirect effects on exports, moderating the positive effects of design relatedness and comparative advantage, and the negative effects of export similarity.

The chapter also investigates the interdependencies between industrial design registration and exports using PVAR modeling. It confirms the interrelationship among overseas design capability, overseas design relatedness, and exports. Existing design capability drives the generation of new design relatedness and future exports. Existing design relatedness encourages new design registrations and exports. The effects differ between variables, with design relatedness playing a larger role in promoting new design registrations, and exports being more affected by design relatedness than the number of design registrations.

Lastly, the study examines the role of global air connectivity in international design collaboration. It finds that air connectivity facilitates international design collaboration, particularly in sectors with high face-to-face communication requirements. Online connectivity complements air connectivity in promoting international design collaboration, as the effect of air connectivity increases with higher levels of online connectivity.

In conclusion, industrial design plays a significant role in the knowledge economy, with its distribution pattern dominated by certain countries. It has a direct and indirect impact on exports, and its interdependencies with exports are confirmed. Additionally, global air connectivity is identified as a driver of international design collaboration, especially in sectors with high face-to-face communication requirements, and online connectivity complements air connectivity in this regard.

Policymakers are urged to identify the policy implications of academic research and industry insights, particularly in the creative industries. Furthermore, the discussion extends to innovation policy in the knowledge-based economy, emphasizing the importance of policies tailored to technologically progressive industries. Design is examined within the context of innovation policy, indicating the need for a modern design perspective in policymaking. Lastly, the transition from the knowledge economy to concerns about automation is explored, revealing shifts in policymakers' focus over time.

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Appendix

List of Owner Countries Covered by Raw Design Data

Owner Country (2-digit ISO)	Owner Country (3-digit ISO)	Owner Country Name
MK	MKD	North Macedonia
GB	GBR	United Kingdom
IT	ITA	Italy
US	USA	United States
AL	ALB	Albania
FR	FRA	France

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study

CH	CHE	Switzerland
DE	DEU	Germany
IE	IRL	Ireland
LU	LUX	Luxembourg
CZ	CZE	Czechia
NL	NLD	Netherlands
LI	LIE	Liechtenstein
ES	ESP	Spain
CN	CHN	China
DK	DNK	Denmark
JP	JPN	Japan
PL	POL	Poland
SE	SWE	Sweden
BR	BRA	Brazil
IN	IND	India
CA	CAN	Canada

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

EE	EST	Estonia
ZA	ZAF	South Africa
BG	BGR	Bulgaria
TR	TUR	Turkey
PT	PRT	Portugal
ZW	ZWE	Zimbabwe
TH	THA	Thailand
TZ	TZA	Tanzania, United Republic of
GH	GHA	Ghana
LS	LSO	Lesotho
KR	KOR	Korea, Republic of
SG	SGP	Singapore
NO	NOR	Norway
CW	CUW	Curaçao
MU	MUS	Mauritius
BE	BEL	Belgium

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

VI	VIR	Virgin Islands, U.S.
HK	HKG	Hong Kong
AU	AUS	Australia
GR	GRC	Greece
MY	MYS	Malaysia
KY	CYM	Cayman Islands
KE	KEN	Kenya
PH	PHL	Philippines
MT	MLT	Malta
EG	EGY	Egypt
VE	VEN	Venezuela, Bolivarian Republic of
MZ	MOZ	Mozambique
NZ	NZL	New Zealand
BJ	BEN	Benin
BW	BWA	Botswana
NG	NGA	Nigeria

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

GM	GMB	Gambia
UG	UGA	Uganda
AE	ARE	United Arab Emirates
TC	TCA	Turks and Caicos Islands
TG	TGO	Togo
BS	BHS	Bahamas
SZ	SWZ	Eswatini
AR	ARG	Argentina
AT	AUT	Austria
AD	AND	Andorra
SK	SVK	Slovakia
HU	HUN	Hungary
IL	ISR	Israel
SI	SVN	Slovenia
MC	MCO	Monaco
NA	NAM	Namibia

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

BZ	BLZ	Belize
FI	FIN	Finland
PN	PCN	Pitcairn
RU	RUS	Russian Federation
BL	BLM	Saint Barthélemy
HR	HRV	Croatia
TV	TUV	Tuvalu
MO	MAC	Macao
SA	SAU	Saudi Arabia
GI	GIB	Gibraltar
UA	UKR	Ukraine
CY	CYP	Cyprus
VU	VUT	Vanuatu
VA	VAT	Holy See (Vatican City State)
TN	TUN	Tunisia
DZ	DZA	Algeria

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

AO	AGO	Angola
AI	AIA	Anguilla
AG	ATG	Antigua and Barbuda
AM	ARM	Armenia
AW	ABW	Aruba
AZ	AZE	Azerbaijan
BH	BHR	Bahrain
BD	BGD	Bangladesh
BB	BRB	Barbados
BY	BLR	Belarus
FO	FRO	Faroe Islands
KP	PRK	Korea, Democratic People's Republic of
PA	PAN	Panama
BA	BIH	Bosnia and Herzegovina
JO	JOR	Jordan
VG	VGB	Virgin Islands, British

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

RO	ROU	Romania
SC	SYC	Seychelles
GG	GGY	Guernsey
MD	MDA	Moldova, Republic of
LB	LBN	Lebanon
BN	BRN	Brunei Darussalam
MX	MEX	Mexico
CL	CHL	Chile
ID	IDN	Indonesia
BM	BMU	Bermuda
UY	URY	Uruguay
PR	PRI	Puerto Rico
QA	QAT	Qatar
EC	ECU	Ecuador
MA	MAR	Morocco
PY	PRY	Paraguay

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

CO	COL	Colombia
ME	MNE	Montenegro
VN	VNM	Viet Nam
SB	SLB	Solomon Islands
IM	IMN	Isle of Man
GT	GTM	Guatemala
DO	DOM	Dominican Republic
AS	ASM	American Samoa
CR	CRI	Costa Rica
JE	JEY	Jersey
KW	KWT	Kuwait
RS	SRB	Serbia
OM	OMN	Oman
IS	ISL	Iceland
LK	LKA	Sri Lanka
SR	SUR	Suriname

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

LV	LVA	Latvia
RE	REU	Réunion
LT	LTU	Lithuania
GD	GRD	Grenada
BO	BOL	Bolivia
WS	WSM	Samoa
BT	BTN	Bhutan
PG	PNG	Papua New Guinea
PE	PER	Peru
NE	NER	Niger
KN	KNA	Saint Kitts and Nevis
TO	TON	Tonga
GE	GEO	Georgia
TM	TKM	Turkmenistan
JM	JAM	Jamaica
NC	NCL	New Caledonia

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

CK	COK	Cook Islands
VC	VCT	Saint Vincent and the Grenadines
GF	GUF	French Guiana
HN	HND	Honduras
SN	SEN	Senegal
AF	AFG	Afghanistan
LR	LBR	Liberia
HT	HTI	Haiti
KI	KIR	Kiribati
GA	GAB	Gabon
MN	MNG	Mongolia
ZM	ZMB	Zambia
SY	SYR	Syrian Arab Republic
IR	IRN	Iran, Islamic Republic of
TT	TTO	Trinidad and Tobago
LC	LCA	Saint Lucia

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

SH	SHN	Saint Helena, Ascension and Tristan da Cunha
KG	KGZ	Kyrgyzstan
MH	MHL	Marshall Islands
IQ	IRQ	Iraq
PK	PAK	Pakistan
YE	YEM	Yemen
UZ	UZB	Uzbekistan
MM	MMR	Myanmar
SM	SMR	San Marino
CU	CUB	Cuba
TK	TKL	Tokelau
ST	STP	Sao Tome and Principe
GL	GRL	Greenland
SD	SDN	Sudan
MS	MSR	Montserrat

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

SL	SLE	Sierra Leone
BF	BFA	Burkina Faso
CF	CAF	Central African Republic
CG	COG	Congo
CI	CIV	Ivory Coast
CM	CMR	Cameroon
DJ	DJI	Djibouti
DM	DMA	Dominica
GN	GIN	Guinea
GQ	GNQ	Equatorial Guinea
GW	GNB	Guinea-Bissau
KH	KHM	Cambodia
KM	COM	Comoros
KZ	KAZ	Kazakhstan
LA	LAO	Lao People's Democratic Republic
LY	LBY	Libya

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

MG	MDG	Madagascar
ML	MLI	Mali
MR	MRT	Mauritania
MW	MWI	Malawi
NI	NIC	Nicaragua
RW	RWA	Rwanda
SV	SLV	El Salvador
TD	TCD	Chad
TJ	TJK	Tajikistan
TL	TLS	Timor-Leste
MV	MDV	Maldives
GY	GUY	Guyana
GU	GUM	Guam
GP	GLP	Guadeloupe
MQ	MTQ	Martinique
YT	MYT	Mayotte

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

MF	MAF	Saint Martin (French part)
AX	ALA	Åland Islands
PM	SPM	Saint Pierre and Miquelon
SX	SXM	Sint Maarten (Dutch part)
WF	WLF	Wallis and Futuna
PF	PYF	French Polynesia
TF	ATF	French Southern Territories
IO	IOT	British Indian Ocean Territory
FK	FLK	Falkland Islands (Malvinas)
GS	SGS	South Georgia and the South Sandwich Islands
CD	COD	Congo, the Democratic Republic of the
FJ	FJI	Fiji
ER	ERI	Eritrea
ET	ETH	Ethiopia
PS	PSE	Palestine, State of

Continued on next page

Table 7.1: Design Owner Countries Covered by This Study (Continued)

NR	NRU	Nauru
NP	NPL	Nepal
SJ	SJM	Svalbard and Jan Mayen
SS	SSD	South Sudan
FM	FSM	Micronesia, Federated States of
BI	BDI	Burundi
CV	CPV	Cabo Verde
BV	BVT	Bouvet Island
SO	SOM	Somalia
AQ	ATA	Antarctica

Table 7.1: Design Owner Countries Covered by This Study (Continued)

List of Protection Territories Covered by Raw Design Data

Protection Country (2-digit ISO)	Protection Country (3-digit ISO)	Protection Country Name

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study

AD	AND	Andorra
AG	ATG	Antigua and Barbuda
AI	AIA	Anguilla
AL	ALB	Albania
AM	ARM	Armenia
AO	AGO	Angola
AR	ARG	Argentina
AT	AUT	Austria
AU	AUS	Australia
AW	ABW	Aruba
AX	ALA	Åland Islands
AZ	AZE	Azerbaijan
BA	BIH	Bosnia and Herzegovina
BB	BRB	Barbados
BD	BGD	Bangladesh

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

BE	BEL	Belgium
BF	BFA	Burkina Faso
BG	BGR	Bulgaria
BH	BHR	Bahrain
BJ	BEN	Benin
BL	BLM	Saint Barthélemy
BM	BMU	Bermuda
BN	BRN	Brunei Darussalam
BQ	BES	Bonaire, Sint Eustatius and Saba
BR	BRA	Brazil
BS	BHS	Bahamas
BW	BWA	Botswana
BY	BLR	Belarus
BZ	BLZ	Belize
CA	CAN	Canada

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

CF	CAF	Central African Republic
CG	COG	Congo
CH	CHE	Switzerland
CI	CIV	Ivory Coast
CL	CHL	Chile
CM	CMR	Cameroon
CN	CHN	China
CO	COL	Colombia
CR	CRI	Costa Rica
CU	CUB	Cuba
CW	CUW	Curaçao
CY	CYP	Cyprus
CZ	CZE	Czechia
DE	DEU	Germany
DJ	DJI	Djibouti

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

DK	DNK	Denmark
DM	DMA	Dominica
DO	DOM	Dominican Republic
DZ	DZA	Algeria
EC	ECU	Ecuador
EE	EST	Estonia
EG	EGY	Egypt
ES	ESP	Spain
FI	FIN	Finland
FK	FLK	Falkland Islands (Malvinas)
FR	FRA	France
GA	GAB	Gabon
GB	GBR	United Kingdom
GD	GRD	Grenada
GE	GEO	Georgia

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

GF	GUF	French Guiana
GG	GGY	Guernsey
GH	GHA	Ghana
GI	GIB	Gibraltar
GL	GRL	Greenland
GM	GMB	Gambia
GN	GIN	Guinea
GP	GLP	Guadeloupe
GQ	GNQ	Equatorial Guinea
GR	GRC	Greece
GS	SGS	South Georgia and the South Sandwich Islands
GT	GTM	Guatemala
GW	GNB	Guinea-Bissau
HN	HND	Honduras

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

HR	HRV	Croatia
HU	HUN	Hungary
ID	IDN	Indonesia
IE	IRL	Ireland
IL	ISR	Israel
IN	IND	India
IO	IOT	British Indian Ocean Territory
IR	IRN	Iran, Islamic Republic of
IS	ISL	Iceland
IT	ITA	Italy
JE	JEY	Jersey
JO	JOR	Jordan
JP	JPN	Japan
KE	KEN	Kenya
KG	KGZ	Kyrgyzstan

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

KH	KHM	Cambodia
KM	COM	Comoros
KN	KNA	Saint Kitts and Nevis
KP	PRK	Korea, Democratic People's Republic of
KR	KOR	Korea, Republic of
KW	KWT	Kuwait
KY	CYM	Cayman Islands
KZ	KAZ	Kazakhstan
LA	LAO	Lao People's Democratic Republic
LC	LCA	Saint Lucia
LI	LIE	Liechtenstein
LK	LKA	Sri Lanka
LR	LBR	Liberia
LS	LSO	Lesotho
LT	LTU	Lithuania

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

LU	LUX	Luxembourg
LV	LVA	Latvia
LY	LBY	Libya
MA	MAR	Morocco
MC	MCO	Monaco
MD	MDA	Moldova, Republic of
ME	MNE	Montenegro
MF	MAF	Saint Martin (French part)
MG	MDG	Madagascar
MK	MKD	North Macedonia
ML	MLI	Mali
MN	MNG	Mongolia
MO	MAC	Macao
MQ	MTQ	Martinique
MR	MRT	Mauritania

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

MS	MSR	Montserrat
MT	MLT	Malta
MW	MWI	Malawi
MX	MEX	Mexico
MY	MYS	Malaysia
MZ	MOZ	Mozambique
NA	NAM	Namibia
NC	NCL	New Caledonia
NE	NER	Niger
NG	NGA	Nigeria
NI	NIC	Nicaragua
NL	NLD	Netherlands
NO	NOR	Norway
NZ	NZL	New Zealand
OM	OMN	Oman

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

PA	PAN	Panama
PE	PER	Peru
PF	PYF	French Polynesia
PG	PNG	Papua New Guinea
PH	PHL	Philippines
PL	POL	Poland
PM	SPM	Saint Pierre and Miquelon
PN	PCN	Pitcairn
PT	PRT	Portugal
QA	QAT	Qatar
RE	REU	Réunion
RO	ROU	Romania
RS	SRB	Serbia
RU	RUS	Russian Federation
RW	RWA	Rwanda

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

SA	SAU	Saudi Arabia
SC	SYC	Seychelles
SD	SDN	Sudan
SE	SWE	Sweden
SG	SGP	Singapore
SH	SHN	Saint Helena, Ascension and Tristan da Cunha
SI	SVN	Slovenia
SK	SVK	Slovakia
SL	SLE	Sierra Leone
SM	SMR	San Marino
SN	SEN	Senegal
SR	SUR	Suriname
ST	STP	Sao Tome and Principe
SV	SLV	El Salvador

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

SX	SXM	Sint Maarten (Dutch part)
SY	SYR	Syrian Arab Republic
SZ	SWZ	Eswatini
TC	TCA	Turks and Caicos Islands
TD	TCD	Chad
TF	ATF	French Southern Territories
TG	TGO	Togo
TH	THA	Thailand
TJ	TJK	Tajikistan
TM	TKM	Turkmenistan
TN	TUN	Tunisia
TR	TUR	Turkey
TT	TTO	Trinidad and Tobago
TZ	TZA	Tanzania, United Republic of
UA	UKR	Ukraine

Continued on next page

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

UG	UGA	Uganda
US	USA	United States
UZ	UZB	Uzbekistan
VA	VAT	Holy See (Vatican City State)
VC	VCT	Saint Vincent and the Grenadines
VG	VGB	Virgin Islands, British
VN	VNM	Viet Nam
WF	WLF	Wallis and Futuna
WS	WSM	Samoa
YT	MYT	Mayotte
ZA	ZAF	South Africa
ZM	ZMB	Zambia
ZW	ZWE	Zimbabwe

Table 7.2: Protection Territories of Registered Designs Covered by This Study (Continued)

Classification Concordance: Locarno - HS2017

A significant proportion of methods used to establish concordance between technology and industry employ a co-occurrence matrix logic. This logic is applied whether the objective is to match company names (Schmoch et al., 2003) or keywords (van-Looy et al., 2014) in both classifications. While not all relevant research utilizes the matrix form, Lybbert and Zolas (2012) proposed an algorithm that counts the frequency of links between patents and industries based on keywords. However, it should be noted that these methods essentially present an algorithmic representation of a co-occurrence matrix. Additionally, the matching frequency can also be applied to employment data, where the objective becomes employees (Dorner and Harhoff, 2017). A similar approach can be found in the work of Design Council (2018), which involves matching industrial designs to corresponding sectors (UK SIC) by identifying design occupations within a firm. In summary, this study agrees with the use of a matrix to visualize the calculation formula. The elements to be filled in the matrix are design records for design-industry matching, with company names serving as the medium for matching. The classic matching problem can be resolved through compromise. Creating a keyword database is time-consuming and requires a comprehensive understanding of both classifications. On the other hand, using only the company matrix would introduce larger bias.

Inspired by Design Council (2018), it is possible to establish a correspondence between design sectors and industrial sectors (UK SIC). If the outputs of design sectors can be allocated to industries, it becomes possible to determine the contribution of each industry to design. Thus, the aim is to link the Locarno classification to the UK SIC, based on data from both the FAME and Orbit databases.

The method of linking these two classifications begins with name matching, as the company names in the FAME firm dataset may also appear in the design dataset. In the matched dataset, there are 6,962 unique company names with valid UK SIC codes that can be successfully matched. Among these companies, there are 91,761 entries of industrial design with valid Locarno codes that can be queried in the design dataset. The materials for the concordance consist of these 6,962 companies with 91,761 entries of industrial designs.

It is important to note that the time dimension of design data is ignored during matching. The focus is solely on the owners of each unique design right. For example, if a company registered one design right in 2008 and five design rights in 2018, a total of six design rights would be attributed to this company.

The initial matching is performed using the 5-digit UK SIC code and the 4-digit Locarno code. Three figures need to be counted: the total number of designs under each UK SIC code (N_i), the total number of designs under each Locarno code (N_j), and the total number of designs under each pair of UK SIC i– Locarno j (N_ij).

This generates a ratio that can be used for further linking: $R_ij = N_ij/N_j$

For each Locarno code, R_ij represents the ratio of design rights contributed by industrial sector i to the total number of designs registered in design sector j.

By utilizing this ratio, it becomes possible to calculate the number of designs that should be allocated to corresponding industries. The sum of the allocated number of design rights for a certain industry represents the total number of designs registered by that industry. Therefore, due to the concordance work, the number of designs under each sector is an estimate. The sample for this estimation consists of the 91,761 design terms belonging to 6,962 companies.

After matching via common names, there are 218 4-digit Locarno classes and 558 5-digit UK SIC classes. Therefore, the best way to visualize the logic of this work is through a co-occurrence matrix. For example, consider several unique designs whose owners are classified under a specific UK SIC code, while these designs are distributed across various Locarno classifications. In this case, a matrix can be filled with designs owned by a company belonging to a column name (a unique UK SIC code), with each design also belonging to one or more row names (Locarno codes).

This correspondence represents an n:n concordance with certain ratios that can be applied for various research purposes. From the design side, this work allocates designs in a Locarno class to one or more industrial sectors. The industrial sector absorbs the allocated designs, and it is linked to various Locarno classes through corresponding ratios.

At this stage, the task of establishing correspondence between HS code and Locarno code has not been completed. There is still one step remaining, which is the concordance between the HS code and the UK SIC (2007) code. The next regression section is based on the HS product code. However, the process of linking the HS code to the Locarno code does not require the development of a matching method. This work is based on existing correspondence tables between the SITC code and the UK SIC code (Haveman, 06/08/2021), as well as the correspondence table between the SITC code and the HS code (WITS, 21/09/2020). Thus, it will involve two additional rounds of matching among different classifications.

This is the first attempt to propose a concordance between the classification of design rights (Locarno code) and industries (UK SIC code). At the 4-digit level, UK SIC 2007 is exactly the same as NACE Rev 2. The transformation path is as follows: NACE Rev 2 → ISIC Rev 4 → ISIC Rev 3.1 → ISIC Rev 3 → HS 2007 → HS 2017. Conversion tables for all these classifications can be found from the United Nations Statistics Division (UNSD).

Large proportion of methods for concordance between technology and industry is using a logic of co-occurrence matrix, whatever the objectives are the company names (Schmoch et al., 2003) or the keywords (van-Looy et al., 2014) for description of both classifications. Not all relevant researches are employing the matrix form to present the work, Lybbert and Zolas (2012) provided an algorithm which count the frequency to each link between patent-industry matching based on keywords; nonetheless, the nature of this kind of methods is actually an algorithmic presentation to co-occurrence matrix. Besides, it is also possible to apply the matching frequency to employment data, the objective could become employees (Dorner and Harhoff, 2017); similar idea to this method could be found from Design Council (2018), whose work also involves in matching industrial designs to corresponding sectors (UK SIC) by identifying the design occupations in a firm. Summarising the existing methods, this study agrees with the matrix logic to visualise the calculation formula; the elements to be filled in the matrix are design records in case of design-industry matching; when matching, the medium should be company names. The classic matching problem could be solved by compromise. Creating a keywords database is time consuming, and it needs comprehensive understanding to both classifications. On the other hand, using the company matrix alone would generate larger bias.

Inspired by Design Council (2018), the design sectors actually could have corresponding industrial sectors (UK SIC), therefore, if it is possible to allocate the design sectors outputs to industries, it would become possible to check how many design contributed by each industry. Thus here would like to link the Locarno classification to the UK SIC, this work was based on both FAME and Orbit databases.

The company names which exist in the FAME firm dataset perhaps also in the design dataset, therefore, the method of linking these two classifications starts from name matching. In the matched dataset, there are 6,962 unique companies names with valid UK SIC codes could be successfully matched, in these companies, there are 91,761 entries of industrial design with valid Locarno codes are able to be queried in the design dataset. The materials for the concordance are these 6,962 companies with 91,761 entries of industrial designs.

It should be noted the time dimension of design data would be ignored when matching, the only thing here has be focused on is the owners of each unique design rights. For example, if a company registered one design right in 2008, while it registered 5 design rights in 2018, total six design rights would be distributed to this company.

The 5-digit UK SIC code and the 4-digit Locarno code were employed to initial matching. There are 3 figures need to be counted: the total number of designs under each UKSIC code (N_i), the total number of design under each Locarno code (N_j), the total number of designs under each pair of UKSIC i– Locarno j (N_ij).

Thus there would be a ratior generated for further linking:

$R_ij = N_ij/N_j$

For each Locarno code, R_ij is counting the ratio of how many design rights contributed by industrial sector i to the total number of designs registered in the design sector j.

Utilizing this ratio to calculate how many design should be allocated to corresponding industries, then the sum of allocated number of design rights of a certain industry, is the total number of design that were registered by this industry. Therefore, because of the concordance work, the number of designs under each sector is an estimate; the sample of this estimation is these 91,761 terms of designs which belong to 6,962 companies.

After matching via the common names, there are 218 Locarno classes of 4-digit, 558 UKSIC classes of 5-digit. Thereby if visualizing the logic for this work, the best way should be the co-occurrence matrix. Imagine an example, there are several unique designs, their owners been classified to a specific UKSIC code, meanwhile, these designs distribute across various Locarno classifications. Thus there could be a matrix to be filled by designs that are owned by a company belongs to a columns names (a unique UKSIC code), and also itself belongs to one or more row names (Locarno codes).

This correspondence is a n:n concordance with certain ratios can be applied to different purposes of research. From the design side, this work is allocating designs in a Locarno class to one or more industrial sectors; the industrial sector would absorb the designs allocated, then it is linked by various Locarno classes with corresponding ratio.

To here, the work of the correspondence between HS code and Locarno code has not been done, since there is still one step that is the concordance between the HS code and the UK SIC (2007) code. The next regression section is based on the HS product code. Whereas, the work of linking HS code to Locarno code does not need to build a method to match both, this work is based on existing correspondence table between SITC code and UK SIC code (Haveman, 06/08/2021), and the correspondence table between SITC code and HS code (WITS, 21/09/2020), thus it will involve in 2 more times of matching among different classifications.

This is the first time attempting to propose the concordance between the classification of design rights (Locarno code) to the industries (UK SIC code). At 4-digit level, UK SIC 2007 is exactly same as NACE Rev 2. Then the transformation path is NACE Rev 2 → ISIC Rev 4 → ISIC Rev3.1→ ISIC Rev 3 → HS 2007 → HS 2017. All of these conversion tables could be found from United Nations Statistics Division (UNSD).

Classification Concordance: Locarno Classification - SITC

The conversion of Locarno classification to HS2017 codes is exemplified in Section 6.6. This conversion process relies on the pre-existing correspondence table between Locarno classification and HS2017 codes. The UN Statistics Division provides access to the correspondence table for HS2017 codes and SITC[1]. Consequently, Locarno classes that have been successfully matched with HS2017 codes can be subsequently linked with SITC codes.

Classification Concordance: Locarno Classification and US I-O

To convert the Locarno classification into US I-O sectors, multiple conversions are required. Since there is no existing concordance table for the conversion between the Locarno classification and other sectors or commodities, the first step involves creating a conversion table. This table will establish the relationship between the Locarno classification and sectors or commodities. By utilizing the UK firm data obtained from FAME, the firm names that can be identified in the Orbit industrial design data will be extracted along with the UK SIC codes of the 2007 version. This process will provide a linkage indicating the number of industrial designs in each Locarno class owned by firms belonging to various UK SIC sectors. For this analysis, a sample of 72,594 industrial designs and 6,279 corresponding owner firms is utilized. Finally, the relationship between the Locarno classification and UK SIC sectors is characterized as many-to-many, implying that industrial designs from each Locarno class can be held by firms from multiple sectors. A weighted ratio is generated to indicate the proportion of de-

[1] https://unstats.un.org/unsd/classifications/

signs from each Locarno class that can be allocated to each UK SIC sector.

According to Prosser (2010), at the 4-digit level, UK SIC 2007 is identical to NACE Rev2. Numerous existing correspondence tables have been developed to convert NACE to other classifications. These tables are utilized as a bridge to determine the shortest path towards US I-O. The conversion of US I-O 1997 to HS commodities has already been completed and can be accessed at BEA[2]. However, the concordance table for HS commodities includes alphabetic codes that do not adhere to the standard format for HS codes. Therefore, these codes are excluded before further processing. The concordance table is based on 10-digit HS commodities and includes weighted ratios for allocating commodities to US I-O sectors.

The maximum ratio in the table is 1, indicating that a commodity would be fully allocated to the corresponding US I-O sector. The minimum ratio is 0.05, suggesting that only 5% of a commodity would be aggregated to a corresponding US I-O sector. Since conversions involving HS codes and other classifications typically occur at the 6-digit level, these commodities need to be aggregated accordingly. The corresponding ratios are aggregated using a weighted average. After aggregation, the maximum allocation ratio remains 1, while the minimum ratio is approximately 0.0017, indicating that only 0.17% of a commodity would be allocated.

Furthermore, the existing conversion table does not specify the version of HS com-

[2] https://www.bea.gov/industry/historical-benchmark-input-output-tables

modities to which the US I-O is converted. Therefore, each HS code in this table needs to be retrieved through all versions of HS commodities. Various versions of HS codes are available at UN Comtrade. The total number of HS commodities is 5,112. Among these, 4,752 commodities can be detected in the HS 1992 version, 5,098 commodities in the HS 1996 version, 4,872 in the HS 2002 version, 4,464 in the HS 2007 version, 4,317 in the HS 2012 version, and 4,270 in the HS 2017 version. Moreover, the set of HS commodities that can be detected in other versions is a subset of the HS commodities that can be detected in the 1996 version. This implies that the HS codes in the conversion table for US I-O and HS commodities are for the HS 1996 version. At the very least, HS 1996 is the optimal version for further linking US I-O with other classifications.

Therefore, it can be confirmed that NACE Rev.2 needs to pass through HS 1996 in order to be further transformed into US I-O 1997. The shortest conversion path is as follows: Locarno class (2-digit) $\rightarrow$ NACE Rev. 2 (4-digit) $\rightarrow$ ISIC Rev. 4 (4-digit) $\rightarrow$ ISIC Rev. 3.1 (4-digit) $\rightarrow$ ISIC Rev. 3 (4-digit) $\rightarrow$ HS 1996 (6-digit) $\rightarrow$ US I-O 1997 (6-digit). Finally, 332 US I-O codes (6-digit) can be matched with the Locarno classification (2-digit). Nunn (2007) has provided a total of 222 US I-O codes (6-digit) with contract intensity measures. Among these, 205 US I-O codes have available measures of contract intensity.

Regression Results of Complementary Effect between Physical and Virtual Connectivity

Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML	OLS	PPML
Groups of Obs.	1st Quartile of SCI	1st Quartile of SCI	2nd Quartile of SCI	2nd Quartile of SCI	3nd Quartile of SCI	3nd Quartile of SCI	4th Quartile of SCI	4th Quartile of SCI
Design Complexity	0.0006	0.0289	0.0042	0.0013	-0.0183***	-0.2785***	-0.0223***	-1.1600***
	(0.0013)	(0.0183)	(0.0028)	(0.0247)	(0.0018)	(0.0525)	(0.0018)	(0.0860)
Air Connectivity x Design Complexity	-0.0004**	-0.0146***	-0.0005	-0.0027	0.0014***	0.0260***	0.0018***	0.0908***
	(0.0001)	(0.0023)	(0.0002)	(0.0024)	(0.0001)	(0.0039)	(0.0002)	(0.0065)
Total Trade Value	-0.0004	0.0113	0.0003	0.0129***	0.0007***	0.0418***	-0.0011***	-0.0324
	(0.0002)	(0.0058)	(0.0003)	(0.0037)	(0.0002)	(0.0070)	(0.0002)	(0.0182)
Constant	0.0685***	-0.2327***	0.1070***	0.4338***	0.0808***	-0.3798***	0.0982***	0.7923*
	(0.0020)	(0.0477)	(0.0035)	(0.0493)	(0.0031)	(0.1108)	(0.0028)	(0.3265)
Fixed Effect	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k
Cluster	ijk	ijk	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.4219		0.4910		0.4524		0.4355	
Pseudo R-squared		0.5681		0.6383		0.6001		0.5830
Log-likelihood	66662.5634	-27058.4948	24872.4551	-59221.3000	41510.4358	-44939.6011	60838.9856	-50547.6017
Nbr.Obs	156806	156806	222006	222006	191036	191036	214508	214508

Table 7.3: Regression Results of Complementary Effect between Physical and Virtual Connectivity: Air Connectivity Measured by Number of Passengers, Sectoral Face-to-face Dependence Measured by Design Complexity

Regression Results (Robustness Test) of Complementary Effect Between Physical and Virtual Connectivity (Air Connectivity Measured by Number of Business-class Passnegers)

Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML	OLS	PPML
Groups of Obs.	1st Quartile of SCI	1st Quartile of SCI	2nd Quartile of SCI	2nd Quartile of SCI	3nd Quartile of SCI	3nd Quartile of SCI	4th Quartile of SCI	4th Quartile of SCI
Design Complexity	-0.0020	-0.0374*	0.0058*	0.0364	-0.0116***	-0.0284	-0.0173***	-0.8539***
	(0.0010)	(0.0160)	(0.0024)	(0.0215)	(0.0016)	(0.0491)	(0.0015)	(0.0649)
Air Connectivity x Design Complexity	-0.0001	-0.0081**	-0.0007**	-0.0074**	0.0011***	0.0077	0.0018***	0.0866***
	(0.0001)	(0.0025)	(0.0002)	(0.0025)	(0.0002)	(0.0045)	(0.0002)	(0.0062)
Total Trade Value	-0.0004	0.0113	0.0003	0.0133***	0.0007***	0.0421***	-0.0011***	-0.0319
	(0.0002)	(0.0058)	(0.0003)	(0.0037)	(0.0002)	(0.0070)	(0.0002)	(0.0183)
Constant	0.0685***	-0.2320***	0.1070***	0.4295***	0.0809***	-0.3835***	0.0983***	0.7847*
	(0.0020)	(0.0475)	(0.0035)	(0.0493)	(0.0031)	(0.1110)	(0.0028)	(0.3284)
Fixed Effect	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k
Cluster	ijk	ijk	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.4219		0.4911		0.4524		0.4355	
Pseudo R-squared		0.5680		0.6383		0.5999		0.5828
Log-likelihood	66659.1909	-27066.5550	24876.6540	-59213.5686	41504.2374	-44954.7955	60838.7482	-50572.3552
Nbr.Obs	156806	156806	222006	222006	191036	191036	214508	214508

Table 7.4: Regression Results (Robustness Test) of Complementary Effect between Physical and Virtual Connectivity: Air Connectivity Measured by Number of Business-class Passengers, Sectoral Face-to-face Dependence Measured by Design Complexity

Regression Results (Robustness Test) of Complementary Effect Between Physical and Virtual Connectivity (Sectoral Face-to-face Dependence Measured by Contract Intensity)

Dep.Var	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design	Ln(Nbr.Design)	Nbr.Design
Estimator	OLS	PPML	OLS	PPML	OLS	PPML	OLS	PPML
Groups of Obs.	1st Quartile of SCI	1st Quartile of SCI	2nd Quartile of SCI	2nd Quartile of SCI	3nd Quartile of SCI	3nd Quartile of SCI	4th Quartile of SCI	4th Quartile of SCI
Air Connectivity x Contract Intensity	-0.0099***	0.0760**	0.0029	0.1004***	0.0068***	0.2296***	0.0176***	0.3087***
	(0.0014)	(0.0252)	(0.0024)	(0.0217)	(0.0013)	(0.0452)	(0.0014)	(0.0576)
Total Trade Value	-0.0004	0.0116*	0.0003	0.0125***	0.0008***	0.0386***	-0.0011***	-0.0311
	(0.0002)	(0.0058)	(0.0003)	(0.0037)	(0.0002)	(0.0068)	(0.0002)	(0.0187)
Constant	0.1153***	-0.5401***	0.0895***	-0.2115	0.0349***	-1.9852***	-0.0155	-1.7170***
	(0.0072)	(0.1220)	(0.0151)	(0.1472)	(0.0095)	(0.3461)	(0.0089)	(0.5114)
Fixed Effect	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k	ijt k
Cluster	ijk	ijk	ijk	ijk	ijk	ijk	ijk	ijk
R-squared	0.4227		0.4910		0.4524		0.4364	
Pseudo R-squared		0.5678		0.6388		0.6004		0.5823
Log-likelihood	66766.4674	-27077.7397	24872.5913	-59139.5113	41513.2175	-44899.7437	61002.0863	-50633.0585
Nbr.Obs	156806	156806	222006	222006	191036	191036	214508	214508

Table 7.5: Regression Results (Robustness Test) of Complementary Effect between Physical and Virtual Connectivity: Air Connectivity Measured by Number of Passengers, Sectoral Face-to-face dependence Measured by Contract Intensity