ESSAYS ON GREENING GLOBAL VALUE CHAINS

by

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Abstract

This thesis comprises four studies that investigate the green transition within global value chains, with particular emphasis on the significant role played by eco-innovation. After an overview in Chapter one, Chapter two presents an examination of the prevailing worldwide trends in eco-innovation and collaborative innovation, revealing a significant expansion of eco-innovation, particularly within specific technological areas. The efficiency of eco-innovation depends on its fast international diffusion, with collaborative efforts between economies serving as an opportunity to encourage green transition. This collaboration has the potential to accelerate the pace at which economies may effectively shift towards green transition.

Chapter three focuses on the study of the relationship between Global Value Chains (GVCs) and international technological collaboration, specifically emphasising collaborative eco-inventions at the country level. The findings of our study indicate that there is a positive relationship between trade in intermediate products, trade in final products, total bilateral exports, and exports in domestic value added (DVA) and the growth of collaborative eco-innovation. we also find that the time it takes for trade to stimulate collaborative innovation can vary and that newly industrialising countries such as China are playing a more important role in GVCs and are increasingly help stimulate collaborative eco-innovation.

In the fourth chapter, a comparative analysis is conducted to assess the relative effectiveness of eco-innovation and non-eco innovation with respect to their technological support of future inventions and subsequent diffusion of knowledge. Furthermore, we aim to examine the differences in quality between global collaborative innovation and non-collaborative innovation, along the variations in international knowledge spillover effects. According to our research findings, it has been observed that eco-innovation exhibits a more pronounced impact on the development of future inventions and displays larger knowledge spillover effects when compared to non-eco innovation. Similar findings are observed in the context of collaborative invention.

Chapter five of our study presents our findings about the relationship between eco-innovations in exporting countries and the carbon dioxide (CO2) intensity of their exports. Our analysis specifically focuses on member countries of the Organisation for Economic Co-operation and Development (OECD) and China. The results demonstrate a negative correlation between eco-innovations and CO2 intensity in these countries' exports. The findings of our research demonstrate a U-shaped association between eco-innovations and the carbon dioxide (CO2) intensity associated with trade. Therefore, our results show that eco-innovation has the ability to green trade. The policy implications have been thoroughly examined in each chapter, with the final chapter serving as a conclusive summary.

To the future.

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I've travelled a long journey to present this thesis in front of you.

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Lastly, to the world at large, may peace be its prevailing wind.

Contents

STATEMENT OF PRIOR PUBLICATION **i**

Abstract **ii**

Acknowledgements **v**

Contents **vii**

List of Figures **xii**

List of Tables **xv**

1 Introduction **1**

2 Investment in Innovation: Global Trends, Collaboration, and the Environment **6**

2.1 Introduction 6

2.2 Data and methodology 13

2.2.1 The international patent classification 13

2.2.2 Empirical measures of innovation and international technological collaboration 15

2.3 Trends in innovation and eco-innovation 18

2.4 Trends in international technological collaboration 41

2.5 Innovation and the manufacturing industry 61
2.5.1 Trends in manufacturing innovation 61
2.5.2 Trends in manufacturing collaborative innovation 65
2.6 Conclusions and policy recommendations 69

3 Collaborative Eco-innovation along Global Value Chains: Evidence from OECD countries 75
3.1 Introduction 75
3.2 International Collaboration Innovation 81
3.3 Slicing up Global Value Chains 85
3.4 Data and Stylised Facts 89
3.4.1 Mapping the International Networks of Co-Innovation 91
3.4.2 Stylised fact on Trade 96
3.5 Methodology 103
3.5.1 Gravity Model 103
3.6 Results 106
3.6.1 Base line Results 106
3.6.2 Robustness Checks 113
3.7 Conclusion and Policy Complications 129

4 Patent Quality and the International Diffusion of Green Technologies: The role of Co-Innovation 131
4.1 Introduction 131
4.2 Literature Review 137
4.2.1 Patent quality and knowledge spillovers 138

4.2.2 Knowledge spillovers from eco-innovation 142

4.2.3 Collaboration and geographical knowledge spillovers 146

4.3 Data and Variables 150

4.3.1 Patent data 150

4.3.2 Variables 153

4.4 Exploratory data analysis 162

4.5 Econometric methodology 170

4.6 Empirical findings 173

4.6.1 Base Model Results 173

4.6.2 Robustness Check 190

4.7 Conclusion 201

5 The Impact of Eco-innovation on CO2 Embodied in Trade: Evidence for the Non-linear Relationship between Green Technologies and Carbon Emission 205

5.1 Introduction 205

5.2 Literature Review 211

5.3 Data and Stylised Facts 218

5.3.1 Data 218

5.3.2 Stylised Facts 221

5.4 Methodology 229

5.4.1 Endogeneity 229

5.4.2 Theoretical Model 231

5.5 Empirical Findings 235

5.6 Conclusion and Policy Implications 243

6 Conclusions **247**

References **252**

A Appendix to Chapter Two **285**

A.1 The abbreviations of economies included in the report 286

B Appendix to Chapter Three **289**

B.1 Trade links 289

B.2 Stylised facts of OECD and China 294

B.2.1 Trade 294

B.2.2 Technological collaboration ranks for OECD and China 298

B.3 Countries included in our research 300

B.4 Results of OECD members 302

C Appendix to Chapter Four **318**

C.1 Examples of technologies in each technical field 318

C.2 Examples of green technologies in each gren technical field 320

C.3 Descriptive Statistics 322

C.4 Rank 324

C.5 Other results 336

D Appendix to Chapter Five **343**

D.1 First stage results 343

D.2 Validity test of instrumental variables 356

D.2.1 OECD+China 356

D.2.2 OECD 356

D.3 Countries included in our research 357

List of Figures

2.1 Change in annual CO_2 emissions over time. 10

2.2 Total inventions, eco-innovations, and non-eco-innovations. 20

2.3 Total inventions in each technology field. 21

2.4 Share of inventions from each technology field of the total number of inventions. 23

2.5 Share of eco-innovations of the total inventions. 29

2.6 Total number of eco-innovations by green technology field. 30

2.7 Share of eco-innovations from each technology field of the total inventions and total eco-innovations. 32

2.8 International collaborative innovations, collaborative eco-innovations, and collaborative non-eco-innovations. 42

2.9 Total international collaborative innovations in each technology field. 43

2.10 Total international collaborative eco-innovations in each technology field. . . . 47

2.11 Share of collaborative innovations and collaborative eco-innovations of the total inventions. 53

2.12 Share of total collaborative eco-innovations of the total eco-innovations and total collaborative innovations. 53

2.13 Share of collaborative eco-innovations for each green technology field of the total international collaborative eco-innovations. 54

2.14 The global collaboration network. 59
2.15 The global eco-collaboration network. 60
2.16 Inventions in selected manufacturing industries. 63
2.17 Eco-innovations in selected manufacturing industries. 63
2.18 Number of inventions in selected manufacturing industries. 64
2.19 Collaborative innovations in selected manufacturing industries. 66
2.20 Collaborative eco-innovations in selected manufacturing industries. 66
2.21 The number of collaborative innovations in selected manufacturing industries. 68

3.1 Decomposition of GVC activities 87
3.2 Technological collaboration links among OECD members and China 94
3.3 Eco technological collaboration links among OECD members and China 95
3.4 Bilateral exports among OECD members and their largest trade partners 99
3.5 DVA content of exports transferred among OECD members and their largest trade partners 100
3.6 DVA embodied in foreign final demand transferred among OECD members and their largest trade partners 101
3.7 Origin value-added embodied in exports transferred among OECD members and their largest trade partners 102
3.8 Average value of GVC position index for OECD + China 103

4.1 Forward citation links 158
4.2 The distribution of inventors' country of residence for eco-innovation (top 50) . 166
4.3 The distribution of inventors' country of residence for international collaborative innovation (top 50) 168
4.4 The distribution of inventor countries of forward citations (eco-innovation) . . . 169

4.5 The distribution of inventor countries of forward citations (international collaborative innovation) 170

5.1 Average eco-innovation and average CO2 intensity from 2005 to 2018 222

5.2 Top ten countries of the total number of eco-innovation (average of 2004 to 2017) 225

B.1 Exports of intermediate products 289

B.2 Exports of final products 290

B.3 DVA content of gross exports 291

B.4 DVA embodied in foreign final demand 292

B.5 OVA in gross exports 293

B.6 The rank of exports in intermediate products, exports in final products and total bilateral exports for OECD members and their largest trade partners 294

B.7 The rank of exports in DVA exports, DVA embodied in foreign final demand and OVA export for OECD members and their largest trade partners 296

B.8 The rank of total collaborative innovation, total collaborative eco-innovation and collaborative non-eco innovation for OECD members and China 298

List of Tables

2.1 Top 20 inventor economies and districts globally in terms of technological innovation. 25

2.2 Top 20 inventor economies and districts globally in each technology field. . . . 27

2.3 Top 20 inventor economies and districts globally in terms of eco-technological innovation. 35

2.4 Top 20 inventor economies and districts globally in each green technology field. 36

2.5 RTAs of the top 20 inventor economies and districts based on the WIPO classification. 39

2.6 RTAs of the top 20 inventor economies and districts based on the WIPO Green Inventory List. 40

2.7 Top 20 inventor economy pairs globally in terms of total international collaborative innovations. 45

2.8 Top 20 inventor economy pairs globally in each technological field. 46

2.9 Top 20 inventor pairs globally in terms of total collaborative eco-innovations. . 49

2.10 Top 20 inventor economy pairs in each green technological field. 51

2.11 Specialisation in each technology field (based on the WIPO classification) of the top 20 inventor pairs (the RTA is constructed based on the total collaborative innovations). 56

2.12 Specialisation in each green technology field (based on the WIPO Green Inventory List) of the top 20 inventor pairs (the RTA is constructed based on the total collaborative eco-innovations). 57

3.1 ESTs fields classified according to IPC Green Lists 85
3.2 Summary Statistics 91
3.3 Average marginal effects of exports related variables for OECD members + China (lag1) 109
3.4 Average marginal effects of value-added related variables for OECD members + China (lag1) 110
3.5 Average marginal effects of exports related variables for OECD members + China (lag2) 111
3.6 Average marginal effects of value-added related variables for OECD members + China (lag2) 112
3.7 First stage results of IV for OECD members + China 118
3.8 IV Poisson GMM results of exports related variable for OECD members + China (lag1) 121
3.9 IV Poisson GMM results of value-added related variable for OECD members + China (lag1) 123
3.10 IV Poisson GMM results of exports related variable for OECD members + China (lag2) 125
3.11 IV Poisson GMM results of value-added related variable for OECD members + China (lag2) 127

4.1 Share of eco-innovation and international technological collaboration in total sample 163

4.2 Uneven distribution of innovation in each technology field 165
4.3 TOTAL INNOVATION 181
4.4 HUMAN NECESSITIES 182
4.5 TEXTILES; PAPER 183
4.6 FIXED CONSTRUCTIONS 184
4.7 PERFORMING OPERATIONS; TRANSPORTING 185
4.8 MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING 186
4.9 ELECTRICITY 187
4.10 CHEMISTRY; METALLURGY 188
4.11 PHYSICS 189
4.12 TOTAL INNOVATION (Remove examiner citations) 192
4.13 HUMAN NECESSITIES (Remove examiner citations) 193
4.14 TEXTILES; PAPER (Remove examiner citations) 194
4.15 FIXED CONSTRUCTIONS (Remove examiner citations) 195
4.16 PERFORMING OPERATIONS; TRANSPORTING (Remove examiner citations) 196
4.17 MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING (Remove examiner citations) 197
4.18 ELECTRICITY (Remove examiner citations) 198
4.19 CHEMISTRY; METALLURGY (Remove examiner citations) 199
4.20 PHYSICS (Remove examiner citations) 200

5.1 Descriptive Statistics 220
5.2 Top ten countries in terms of total number of new eco-innovation applications (2004 VS 2017) 225

5.3 Top 10 exporting countries in CO2 intensity in different types of trade (average from 2005 to 2018) 228
5.4 Top 10 trading country-pairs in CO2 intensity in different types of trade (average from 2005 to 2018) 228
5.5 Second stage results of OECD + China 241
5.6 Second stage results of OECD countries 242

B.2 Average marginal effects of exports related variables for OECD members (lag1) 303
B.3 Average marginal effects of value-added related variables for OECD members (lag1) 304
B.4 Average marginal effects of exports related variables for OECD members (lag2) 305
B.5 Average marginal effects of value-added related variables for OECD members (lag2) 306
B.6 First stage results of IV for OECD members 307
B.7 IV Poisson GMM results of exports related variable for OECD members (lag1) 310
B.8 IV Poisson GMM results of value-added related variable for OECD members (lag1) 312
B.9 IV Poisson GMM results of exports related variable for OECD members (lag2) 314
B.10 IV Poisson GMM results of value-added related variable for OECD members (lag2) 316

C.1 Descriptive Statistics 322
C.2 The rank of inventors' residence of countries (regions) (Eco-innovation) 324
C.3 The distribution of inventors' residence of countries (regions) (international collaborative innovation) 327
C.4 Distribution of forward citations by country of inventor, for eco-innovation. . . 330

C.5 Distribution of forward citations by country of inventor, for international collaborative innovation. 333
C.6 Forward citations (only for eco-innovation) (Remove inventor self-citations) . . 337
C.7 International knowledge spillovers (only for eco-innovation) (Remove inventor self-citations) 338
C.8 Forward citations (only for eco-innovation) (Remove inventor & applicants self-citations) 339
C.9 International knowledge spillovers (only for eco-innovation) (Remove inventor & applicants self-citations) 340
C.10 Forward citations (only for eco-innovation) (Remove examiner citations) 341
C.11 International knowledge spillovers (only for eco-innovation) (Remove examiner citations) 342

D.1 First stage results of OECD + China (ECO_i) 344
D.2 First stage results of OECD + China (ECO_j) 347
D.3 First stage results of OECD countries (ECO_i) 350
D.4 First stage results of OECD countries (ECO_j) 353

Chapter 1

Introduction

The global economy has had a number of difficulties over the last few decades, including energy crises, food insecurity, and serious environmental problems. A sustainable set of solutions to the climate change dilemma should be discovered within the context of international cooperation, according to the recent Intergovernmental Panel on Climate Change (IPCC) report (Lynn and Peeva, 2021). In order to encourage sustainable development, green transition has been widely adopted as one of the main channels to solve environmental issues. The traditional "Made in" tags on products are now seen as symbols of the past. Nowadays, many goods are produced through global collaboration. Global value chains (GVCs) refer to the division of production processes into various stages, which are then coordinated and collaborated on across the national borders to maximise production efficiency (Antràs, 2020a). Global value chains (GVCs) are crucial to the process of attaining the green transition, particularly in terms of resilience to external shocks like conflict, natural catastrophes, or other sources of uncertainty. Most importantly, fragmented production has become one of the primary ways in which global value chains propagate pollution, making it imperative to mitigate the pollution issues arising from global value chains.

In the past two decades, there has been a significant development in fragmentation and globalisation of production chains. This may be attributed to the removal of trade barriers, as well as improvements in the international transportation industry and production technologies. Driven by the fragmentation and globalisation of production chains, traditional trade has been profoundly changed by global value chains (GVCs), leading the world into what has been called the 'Age of Global Value Chains' (Antràs and Chor, 2021; Byahut et al., 2021). One of the implications of the fragmentation of production is that products and services can cross borders many times in the form of exports, imports, or transfers of value-added (Baldwin and Venables, 2013; Raei, Ignatenko, and Mircheva, 2019). Therefore, the globalisation of production processes and the resulting increase in international trade has important environmental implications (Christoff and Eckersley, 2013; D. I. Stern, 2017). This is the underlying reason why GVCs lead to serious pollution problems not just because of the increased production resulting from trade, but also because fragmented production spreads pollution to every corner of the value chain.

We need to mitigate environmental pollution issues, and trade often contributes significantly to pollution. One of the solutions to mitigate the environmental issue during production is through adopting eco-innovation, defined as innovations that could prevent pollution, save energy and protect the environment during production (Sinclair-Desgagné, 2013). However, the eco-innovation process is complex and requires a broad range of skills, knowledge and technological inputs (Barbieri, Marzucchi, and Rizzo, 2020). The intricate nature of eco-innovation is a key reason why international collaboration is frequently emphasised as one of the primary means for developing technology, especially for environmental technologies. However, to date, there is little research on understanding collaborative eco-innovation and how it will be stimulated in the context of GVCs. Can new eco-innovation effectively mitigate the environmental damage resulting from trade activities and facilitate the integration of sustainable activities within global value chains? We conducted research on this question, organised into four main chapters.

Chapter Two of the thesis investigates the expansion of eco-innovation on a global scale, spanning the years 1995 to 2019, with a substantial sample size of over one billion. By addressing the disparities in development across different technological fields, the results highlight the significant challenges that the entire world is currently dealing with, with a prominent concentration on the issue of climate change and its immediate and broader economic consequences. Chapter two also discusses barriers to technology diffusion and emphasises the potential benefits of international collaboration in developing green technologies. This chapter also emphasises the significance of collaboration in promoting the worldwide diffusion of green technologies, as well as the crucial role of policies for such technologies.

The main goal of Chapter Three is to explore how (GVCs) are related to international collaboration and innovation in the field of green technologies, by focusing on OECD member countries and their significant trade partner, China. We use various trade-related measures to study how participating in GVCs impacts collaborative eco-innovation. The results show that trade can stimulate collaborative eco-innovation, whether the trade partners have a direct trade relationship. Our study includes both developed and developing countries. These findings suggest that cooperation within GVCs helps strengthen collaborative eco-innovation among trading partners. Eco-innovation is widely recognised as requiring significant funding, technological support, and policy backing, which are often lacking in developing countries. While trade can lead to pollution, the exchange of tangible and intangible knowledge through traded goods and services provides developing countries with incentives for eco-innovation and the greening of value chains.

Chapter Four investigates the quality of eco-innovation and collaborative innovation, as well as their knowledge spillover effects. By analysing simple patent families first filed in the United States from 2000 to 2016, we proved that, compared to non-eco-innovation, eco-innovation exhibits higher quality. This is evident from higher forward citation counts, indicating its ability to better guide future inventions. At the same time, our findings demonstrate that, in comparison to non-eco-innovation, eco-innovation has a stronger ability to globally disseminate knowledge, showing more robust knowledge spillover effects. Similar conclusions were drawn from the analysis of collaborative innovation. We also conducted separate analyses for eight different technological fields, examining the quality and knowledge spillover effects of eco-innovation and collaborative innovation in each field.

Chapter Five explores the relationship between eco-innovation, carbon emissions, and international trade. Eco-innovation is recognised as an effective solution for addressing environmental challenges, particularly in reducing carbon dioxide (CO2) emissions. These technologies have the potential to reduce emissions without hindering economic growth and can be applied across various sectors such as renewable energy, waste management, and pollution control. This study uses the intensity of CO2 embodied in trade as a metric and the number of green technologies as an indicator to assess eco-innovation across countries. The research covers OECD member countries and China, emphasising their roles as significant contributors to both emissions and innovation. The study identifies a non-linear relationship between trade-related emissions and eco-innovation, highlighting that while adopting green technologies reduces carbon intensity embodied in trade, the further development of eco-innovation may not lead to additional emission reductions, potentially due to diminishing returns or technology maturity.

In conclusion, this study yields significant insights into the environmental issues in GVCs and raises the potential solution. We show that both eco-innovation and collaborative innovation exhibit robust cross-border knowledge spillover effects. Moreover, they possess a remarkable capacity to provide valuable technical guidance for future inventions. As discussed earlier, eco-innovation poses significant challenges for developing countries. However, our research demonstrates that cooperation in trade can not only lead to pollution but can also incentivise eco-innovation, particularly collaborative eco-innovation, with strong knowledge spillover effects. Through international trade, developing countries can foster partnerships with developed countries, thereby facilitating the transfer of knowledge and enhancing their capabilities of eco-innovation. All of this provides crucial empirical evidence for crafting incentives for green transition in developing countries. Lastly, we've demonstrated the tangible benefits of eco-innovation in greening global value chains. This is exemplified by the significant reduction in CO2 intensity embodied in trade resulting from eco-innovation by exporters. Therefore, our thesis presents a unique viewpoint and provides valuable empirical guidance for the greening of global value chains.

The last chapter concludes the main findings and discusses the policy implications. Following the discussion of the limitations of the thesis, future work is suggested.

Chapter 2

Investment in Innovation: Global Trends, Collaboration, and the Environment

2.1 Introduction

The global economy is facing a number of challenges, perhaps the most important of which is climate change, which has immediate but also broader economic and geo-political implications. Whether it is the energy crisis, food security, or migration patterns, one could argue that the changing climate will play an increasingly important role. For example, the latest Intergovernmental Panel on Climate Change (IPCC) report highlights that it is imperative that action is taken to tackle the climate change crisis and argues that international cooperation is essential if we are to find sustainable solutions (Lynn and Peeva, 2021). Environmental concerns are already global concerns that cannot be solved by a single economy acting alone but require cooperation at a global scale (Haščič, Johnstone, and Kahrobaie, 2012). For example, some regions, including developing Asia and the Pacific, have put forward plans for a green transition that aim to put their economies on a more sustainable growth path. Central to the transition story is the role played by global value chains (GVCs) and how resilient these GVCs are to external shocks from, for example, war, natural disasters, or pandemics and where firms face generally increased risk and uncertainty.

It is widely understood that a core element of any green transition is technological innovation and the development of climate change mitigation technologies (Ph Aghion, Hemous, and Veugelers, 2009; K.-H. Lee and Min, 2015).[1] Although innovation per se can have environmental benefits (machines that can produce more widgets per hour may also be more energy efficient), within the context of a green transition the emphasis is often on the promotion of eco-innovation and more recently the promotion of collaborative eco-innovation between different economies.[2] If economies are to make a successful green transition, it has been argued that government support for eco-innovation by way of subsides and fiscal policy is required. However, because there is often a lag between R&D expenditures and the actual innovation, governments tend to be reluctant to allocate funds to stimulating green technologies (J. Yang, Jeong, and Cheon, 2011).

Hence, despite promising a post-COVID green transition, many economies are struggling to meet these goals in the face of the current global energy crisis and geo-political tensions. For example, O'Callaghan and Murdock (2021) analyse the COVID-related fiscal policies of about 50 major economies and shows that only \$386 billion of the \$46 trillion spent in 2020 was considered green and sustainable, so that only around 18% of the world's major economies' expenditures for economic recovery after the epidemic was for green projects. One possible

[1]Technological innovation refers to the innovation of production technology, including the development of new technologies or a new application of an existing technology (Baden-Fuller and Haefliger, 2013). It is important to distinguish between technological innovation and research and development (R&D); R&D is thought of as the early stages of the innovation process that provide the investment in material and scientific knowledge necessary for later innovation success (Oltra, René Kemp, and De Vries, 2010).

[2]In the literature, eco-innovation is also called green innovation or environmental innovation and is usually defined as any technological innovation or breakthrough that could reduce environmental pollution or any detrimental effects on the environment of the manufacturing process (Oltra, René Kemp, and De Vries, 2010).

explanation is linked to the current green jobs debate on how eco-innovation is related to job creation in new green sectors and possible job destruction in traditional heavy industry (Elliott, Kuai, et al., 2021). However, more generally, support for eco-innovation has been shown to bring long-term benefits, and it is argued that it helps economies develop greater domestic R&D capabilities (OECD, 2009; Antal, 2014). However, the current economic and political environment is causing some concern, especially as we move into the winter of 2022 and economies are looking carefully at how they will be able to keep the lights on. Although in the short term we may see renewed investment in coal-fired power stations, this may also spur a longer-term push for more support for renewable energy as a source of power.

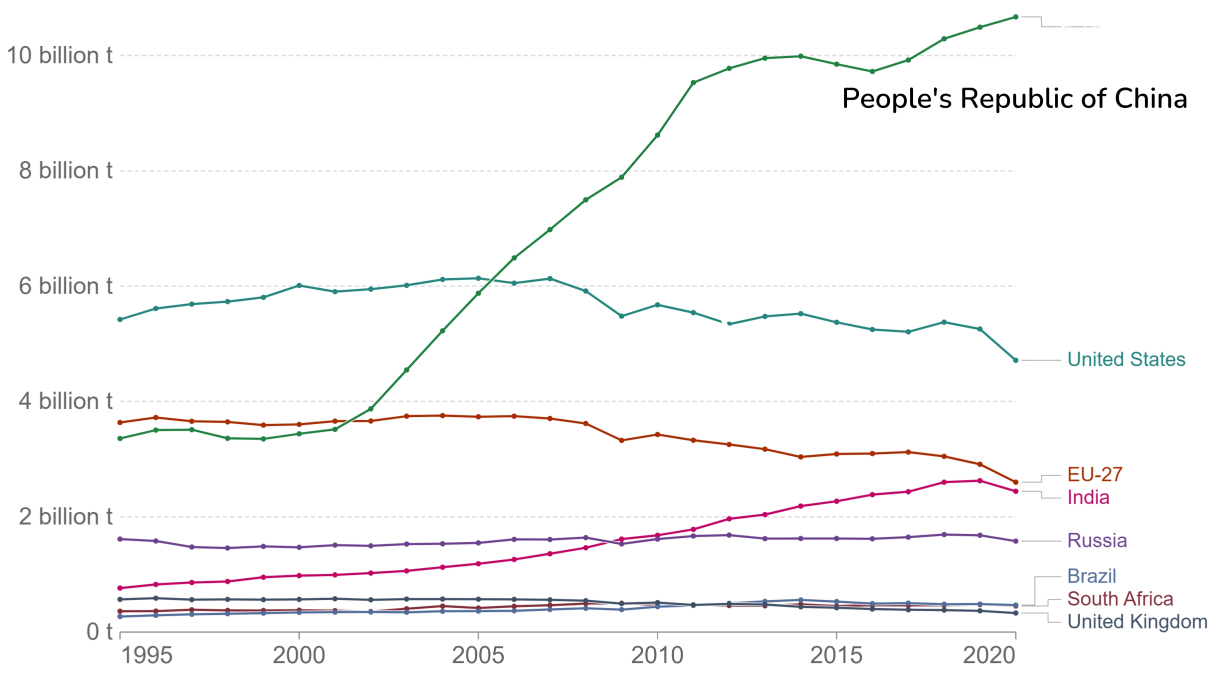
An important aspect of the global push for greater investment in eco-innovation, whether through private or public sector investment, is the potential for the rapid diffusion of these new green technologies in the hope that this will lead to significant environmental spillovers and a subsequent reduction in global CO_2 emissions. However, there are considerable barriers to technological diffusion that need to be overcome (Jacobsson and Johnson, 2000; Strupeit and Palm, 2016). These challenges include issues related to intellectual property, patent laws, and the absorptive capacity of economies to be able to incorporate advanced green technologies into their current manufacturing base and overall infrastructure (e.g., transport and power supply sectors). One way in which diffusion can be accelerated is thought to be through international collaboration in the development of green technologies. To understand the role that so-called collaborative eco-innovation may play in future green technological diffusion, it is important to understand recent trends in both innovation and collaborative innovation.

The underlying motivation for this paper is to get a better understanding of whether a more effective diffusion of green technologies can be achieved through active support for a greater degree of eco-innovation to be initiated through international cooperation between research teams. Our approach is to examine whether the period of rapid globalisation between 2000 and 2020 (which includes the People's Republic of China's entry into the World Trade Organisation (WTO)) has led to a greater degree of cooperation in the development of green technologies or whether eco-innovation remains the domain of developed economies either acting alone or within groups of economies, such as the Organisation for Economic Co-operation and Development (OECD) (Haščič, Johnstone, and Kahrobaie, 2012).

The importance of promoting the effective diffusion of green technologies between developed and developing economies is highlighted by an examination of the recent growth in global emissions, which shows that the growth comes overwhelmingly from developing economies (Copeland, J. S. Shapiro, and M. Scott Taylor, 2021). Between 1995 and 2020, annual carbon emissions grew significantly, led by rapid increases from China and India, while emissions in some developed economies were relatively flat or even, in the case of Sweden, decreased.[3] Figure 2.1 shows, for example, the growing carbon emissions for China and India, with the former being the world's largest polluter since 2005. Carbon emissions in the United States and European economies have been flat or decreased over this period. However, it is important to remember how emissions can be contained in imports and exports and are transported along global value chains. A figure of carbon emissions per capita would also show a very different picture, albeit with fairly similar growth paths.

[3] Annual carbon dioxide emissions are calculated from the burning of fossil fuels for energy and cement production.

Figure 2.1: Change in annual CO_2 emissions over time.



Source: CO_2 emissions data are sourced from the Global Carbon Project and Carbon Dioxide Information Analysis Center (CDIAC) (https://data.ess-dive.lbl.gov/portals/CDIAC/Data [accessed October 2022]).

Despite being the primary source of current carbon emissions, not surprisingly, developing economies still lag behind developed economies when it comes to eco-innovation leadership. There are a number of reasons for this relative lack of leadership, including the lack of workers with the appropriate skills, limited R&D capacity, and low investment rates in R&D (Cirera and Maloney, 2017). Policies to strengthen eco-innovation in developing economies could be argued to be a core solution to climate-related challenges. One of the first steps may be the encouragement of collaborative eco-innovation and hence documenting these trends is one of the motivations for this paper.

When we discuss the concept of international cooperation for green technologies, it is important that it is framed in the context of globalised and fragmented value chains. The fragmentation of production value chains generalises a connection between the production and consumption of emissions, and spreads the emissions along the whole chain. A potentially important causal relationship that needs further investigation is related to understanding whether cooperation between the trade partners helps to stimulate eco-innovation and hence accelerate a global green transition through the more rapid diffusion of green technologies between economies and from developed to developing economies (Duan, Nie, and Coakes, 2010; D. B. Audretsch, Lehmann, and Wright, 2014; Minas, 2018).

There are a number of existing studies on international technological collaboration (De Prato and Nepelski, 2014; Xuefeng Wang et al., 2014; Y. Liu et al., 2018).[4] Some existing studies are based on the case study of a single economy; for example, De Prato and Nepelski (2014) show that economies are more likely to cooperate if they share the same official language, are geographically closer, or are closer in terms of cultural proximity. However, the existing research tends to focus on developed economies and ignores developing economies' participation in collaborative innovation (Truskolaski, 2012; Xuefeng Wang et al., 2014).

There are a number of approaches that policymakers can take to encourage eco-innovation. The most popular can be thought of as the carrot of R&D subsidies (René Kemp, 2000) and the stick of environmental regulation (Horbach, Rammer, and Rennings, 2012). However, whether these solutions will also act as a driver of international collaboration in eco-technological innovation is little understood. From a policy perspective, it is also argued that policies need to focus on the number of innovations across different fields, guide the direction that the research should

[4]In the majority of studies, international technological collaboration is defined as collaborative innovation when an invention has more than one inventor and the inventors declare different economies of residence (Haščič and Migotto, 2015a).

take, and also act as a regulator when needed (Haščič and Migotto, 2015a).

The purpose of this paper is to provide an overview of the global trends in eco-innovation and collaborative eco-innovation. The paper also includes a mapping exercise in which we illustrate the extent to which trends in international technological collaboration have changed over time. We also provide some practical guidance for policymakers and describe how to formulate policies to encourage collaborative innovation and collaborative eco-innovation. More specifically, we document trends in global innovation across different technology fields or industries and cooperation patterns across economies. Furthermore, we document progress in international collaborative eco-innovation to try to understand why there are different trends in eco-collaborative innovation across different technology fields. We believe that before we design the appropriate policies, it is important to understand existing trends, patterns, and networks of international collaborative eco-innovation and how this contributes to the resilience of GVCs more generally.

The approach we take in this paper on international technological innovation is to use patent-based data. Patent data provide rich information about an invention, including the inventor(s), applicant(s), invention time, and a range of other factors. Using the definition of environmentally sound technologies (ESTs) from the United Nations Environmental Programme (UNEP), we are able to use international collaborative innovation patent data to distinguish between eco- and non-eco-innovations.[5] Previous studies have used the classification from the OECD, which classifies ESTs into three types: (1) environmental-related technologies, (2) climate change

[5]Environmentally sound technologies refer to those technologies that can protect the environment by decreasing waste and reducing pollution and have the potential to improve environmental performance. For details, see https://www.unep.org/regions/asia-and-pacific/regional-initiatives/supporting-resource-efficiency/environmentally-sound (accessed 10 October 2022).

adaption technologies, and (3) sustainable ocean economy technologies. Expanding on previous studies, we will use UNEP's classification of green technologies, which are classified by production activities and product use rather than the impact on the environment. For example, the technologies of hybrid vehicles are categorised as 'transportation' in our research but are classified as 'climate change mitigation technologies' based on the OECD classification.

The remainder of the paper is organised as follows. Section two describes the source of the data, our methodological approach to measuring innovation, and the strategies used to define and distinguish between innovation and eco-innovation. Sections three and four describe the development of technological innovation and international technological collaboration. The development of eco-innovation, international collaborative eco-innovation, and the uneven development issues in different technology fields are also explained. Section five presents the development of green technologies across the manufacturing sector. Section six concludes this paper and discusses a range of policy recommendations that are relevant to developing Asia and the Pacific and contribute to the debate on how to foster more GVCs in the face of increasing risk and uncertainty.

2.2 Data and methodology

2.2.1 The international patent classification

The main source of data used in this paper is PATSTAT, where patent information is categorised according to the International Patent Classification (IPC) system. The IPC system was created to enable users to identify patents across different technological fields. IPC codes have been applied by over 100 economies to group patents regardless of the language used in the patent application document. An invention can be assigned more than one IPC code depending on its function and the field of application. Hence, the IPC system has been designed to be a combined function-application classification system (OECD, 2009).[6] In addition, an IPC class, when combined with the Statistical classification of economic activities in the European Community (NACE) REV.2 code, can be used to count the number of inventions in different industries or sectors.[7]

One of the main benefits of IPC codes is that they can be used to identify eco-innovations. The 'IPC Green List' developed by the IPC Committee of Experts allows users to search for patent information related to environmentally sound technologies (ESTs) that are listed in the United Nations Framework Convention on Climate Change (UNFCCC). There are seven green technical fields, each of which is assigned several green IPC codes. Our research is conducted using the entire green IPC list.[8] It should be noted that a patent may be assigned several IPC codes, which may include green and non-green codes. If the invention information (contribution to the prior art) contained in such a patent filing is classified as 'green-related' in the IPC Green Inventory Scheme, this invention is classified as an 'eco'-invention, even though there may exist other technical features contained in this invention that are excluded by the Green Inventory Scheme (León et al., 2018).

[6]According to our data, about 23.4% of inventions have at least two 4-digit IPC classes.

[7]The IPC-NACE concordance table has been updated by the World Intellectual Property Organisation (WIPO). The inventions are categorised based on their manufacturing industry according to the IPC-NACE concordance table. For example, an invention related to agriculture may be classified in the category called the manufacture of food products, beverages, and tobacco products.

[8]The complete list of EST classifications categorised by WIPO can be accessed at https://www.wipo.int/classifications/ipc/green-inventory/home (accessed 10 October 2022).

2.2.2 Empirical measures of innovation and international technological collaboration

The literature on eco-innovation adopts a variety of methods to measure different aspects of innovation. Eco-innovation can be identified from the 'effect' perspective, which refers to innovations that can reduce the use of natural resources or achieve environmental sustainability (René Kemp and Pearson, 2007; Carrillo-Hermosilla, Del Río, and Könnölä, 2010). Measures of eco-innovation include (1) a simple count of environmental patents (Brunnermeier and Cohen, 2003; Carrión-Flores and Innes, 2010), (2) counts of eco-innovations (Haščič, Johnstone, and Kahrobaie, 2012), and (3) measures of how effective technologies are in reducing energy use or pollution (De Marchi, 2012). Eco-innovation can also be identified from an 'input' perspective. Examples include (1) the green R&D expenditure (Koçak and Ulucak, 2019) and (2) R&D personnel and innovation expenditure (including the intangible investments such as the design expenditure) (Hall and Josh Lerner, 2010). Each measure has its own strengths and weaknesses. For example, the R&D expenditure only reflects investment, such as resources devoted to producing innovation, but does not capture the outcome of the innovation process. Likewise, the ability of an innovation to reduce pollution does not tell us how much pollution has been reduced. On balance, we believe that the number of eco-innovations is a good proxy of the eco-innovation activity, as it captures the result or output of investment in innovation directly (Hall and Josh Lerner, 2010).

The patent data we use come from the PATSTAT database (2022 spring edition) and cover the period 1995 to 2020. PATSTAT contains more than 100 million patent documents collected from more than 90 patent offices internationally (De Rassenfosse, Dernis, and Boedt, 2014). Patent records include information on inventors' addresses, application dates, application IDs, and other information related to patent classification. There is also information on legal events for the more than 40 patent offices that are included in the European Patent Office (EPO) Global Legal Event Data (INPADOC). It is worth providing a short reminder of the advantages of patent data:

- The R&D expenditure and scientific publications only take the input of the inventive process into account. Patent data, on the other hand, are a direct measure of innovation, as these data focus on the outputs of the invention process (Haščič and Migotto, 2015a).
- Patent documentation provides a wealth of information related to the innovation process. In our case, where the innovation took place is important to understanding the degree to which innovation is a result of international technological collaboration.
- Patent data can be disaggregated into different technology fields or sectors and classified into various green technology fields. Details concerning green technology fields and their representative technologies are provided in the Appendix. The use of technology fields gives us the opportunity to study eco-innovation and collaborative eco-innovation at a disaggregated level and to analyse the patterns and trends of collaborative innovation in the different technological areas.

However, there are also limitations associated with the use of patent data that are worth recapping briefly:

- Not all inventions are patented (Haščič and Migotto, 2015a). Many 'inventions', such as copyrighted items, are included in intellectual property right (IPR) regimes but are not patented in the patent office.
- Not all the patented inventions are of 'good quality'. The quality of a patent is related to the importance of the invention, its commercial value, or the possibility of this invention

being maintained after the patent is enforced (Squicciarini, Dernis, and C. Criscuolo, 2013). Patent litigation refers to all litigation related to patents and is an expensive process. If an enterprise, or individual, goes to considerable expense to protect a patent, it shows that the patent is expected to have a commercial value that exceeds the litigation cost (Lanjouw and Schankerman, 2001). The patent quality is a good indicator of the link between innovation, technology diffusion, and social and economic development (Squicciarini, Dernis, and C. Criscuolo, 2013). The patent records provide information related to quality, including the family size, the number of IPC codes, the lag between the application and granting of the patent, forward citations, and backward citations.[9]

- Unfortunately it is not possible for researchers to exclude inventions whose inventors are located in different places but have the same nationality. Similarly, it is not possible to filter out inventions that have been developed by two laboratories that are located in different places but belong to the same firm (Squicciarini, Dernis, and C. Criscuolo, 2013).

After describing some of the benefits and challenges of using patent data, we now describe how we use the patent data to develop our measures of innovation and international collaborative innovation. Our measure of the number of innovations is constructed from simple frequency counts. An invention is considered to be the result of international technological collaboration if it has more than one inventor and its inventors reside in different economies. To avoid any double-counting problem, we calculate the total number of simple patent families instead of the number of patent applications.[10] A simple patent family may have multiple IPC codes because

[9]In terms of the Paris Convention (1883), applicants have no more than 12 months from the earliest filing date to file applications and claim the priority date of the first application in patent offices located in other economies for the same invention. The number of patent offices that protect the same invention is the family size. The patent family size may suffer from timeliness issues because different economies have different requirements regarding the time from the filing date to the earliest application needed to claim the priority date for any following application.

[10]A patent family is a set of patent applications of one specific invention or similar technologies. Members of a simple patent family are all related to the same invention (Park, Hingley, et al., 2009). When calculating the total number of inventions, we try to stay in the patent family realm.

the invention could be categorised into different technology fields. When counting the total number of simple patent families of a specific technology field, each simple patent family is only counted once. For example, an invention related to solar energy may be classified under two sub-classifications: ‘solar concentrators’ and ‘use of solar heat’. However, when calculating the total number of inventions related to solar energy, this invention will be counted only once. Moreover, a distinction can also be drawn between eco-patent families and non-eco-patent families based on the green IPC code listings.

From the PATSTAT database, we rely on the following information:

- Patent family ID: ID number used to identify the patent family;
- Priority date: The earliest filing date, which is used to identify the earliest filing year of an invention;
- Publication date: The earliest publication date;
- Inventors’ residence economies: The economies of residence of the inventor(s), which are used to identify international co-invented patents;
- IPC codes: Used to categorise an invention as a eco-innovation and to more generally classify patents into different technology fields and manufacturing sectors.

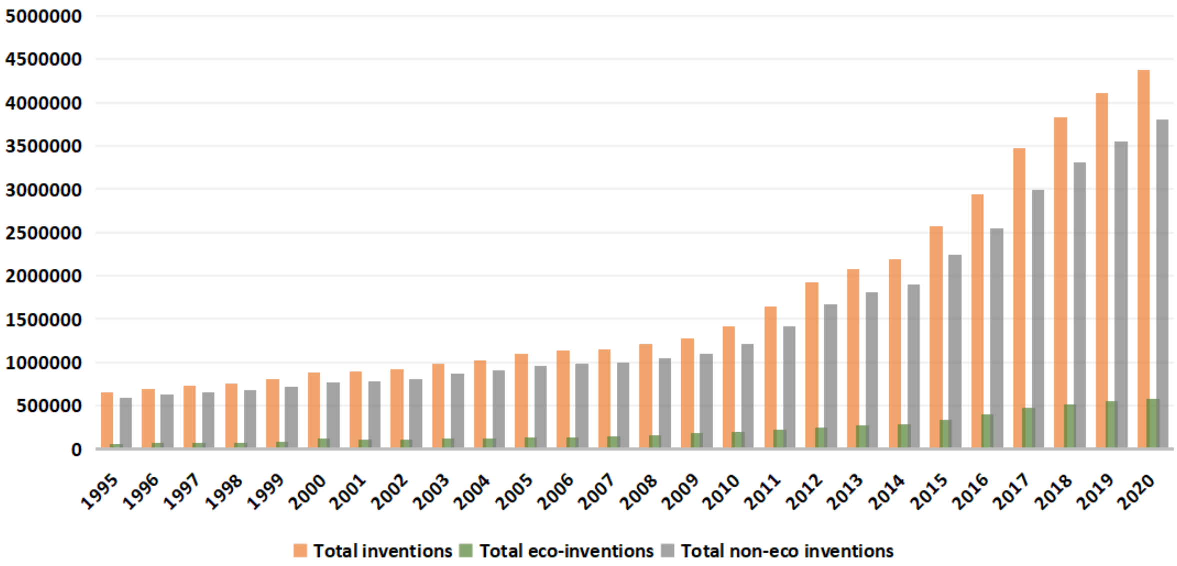
2.3 Trends in innovation and eco-innovation

We examine trends in innovation between 1995 and 2020. After dropping equivalent inventions, i.e., counting the total number of simple patent families and dropping patent families with the same identification codes, we obtain records on more than 3 billion inventions of which over 4 million are eco-innovations. Figure 2.2 presents the trends in total inventions, eco-innovations, and non-eco-innovations over the last 26 years. Starting in 1995, the general trend is upwards, with no real slowdown during the financial crisis between 2007 and 2009. For example, on 11 February 2009, the United States (US) passed an economic stimulus plan that released 789 billion US dollars to get the economy back on track. As a result, investment in basic research, biomedical research, energy research, and climate change mitigation projects reached record highs (Obama, 2011).

In the same year, Germany (GE), France (FR), and the United Kingdom (UK) also attempted to boost their economies by stimulating high-tech research (Andersen, 2009). In terms of eco-innovation, in June 2009, the US passed the 'Clean Energy and Security Act' (ACESA), while Germany announced that developing clean energy technologies would be a priority area of research (Lehr, Lutz, and D. Edler, 2012). At the same time, several developing economies, such as China (CN) and India (IN), also started to pay more attention to eco-technological innovation, especially innovation related to alternative energy (Kumar et al., 2010; T. Liu et al., 2011). Figure 2.2 shows that the speed of innovation appears to increase after 2009, highlighting the degree to which economies increasingly recognise the importance of innovation both to create economic growth and also, in the case of eco-innovation, to solve environmental issues.

The total number of inventions, eco-innovations, and non-eco-innovations reached 4,375,700, 576,684, and 3,799,016, respectively, in 2020. Even the shock of the COVID pandemic appeared to do little to slow down the pace of innovation.

Figure 2.2: Total inventions, eco-innovations, and non-eco-innovations.



Source: Authors' calculations based on PATSTAT data.

Figure 2.3 presents a count of inventions by technology field between 1995 and 2020. There are eight types of technology fields according to the World Intellectual Property Organisation (WIPO):[11]

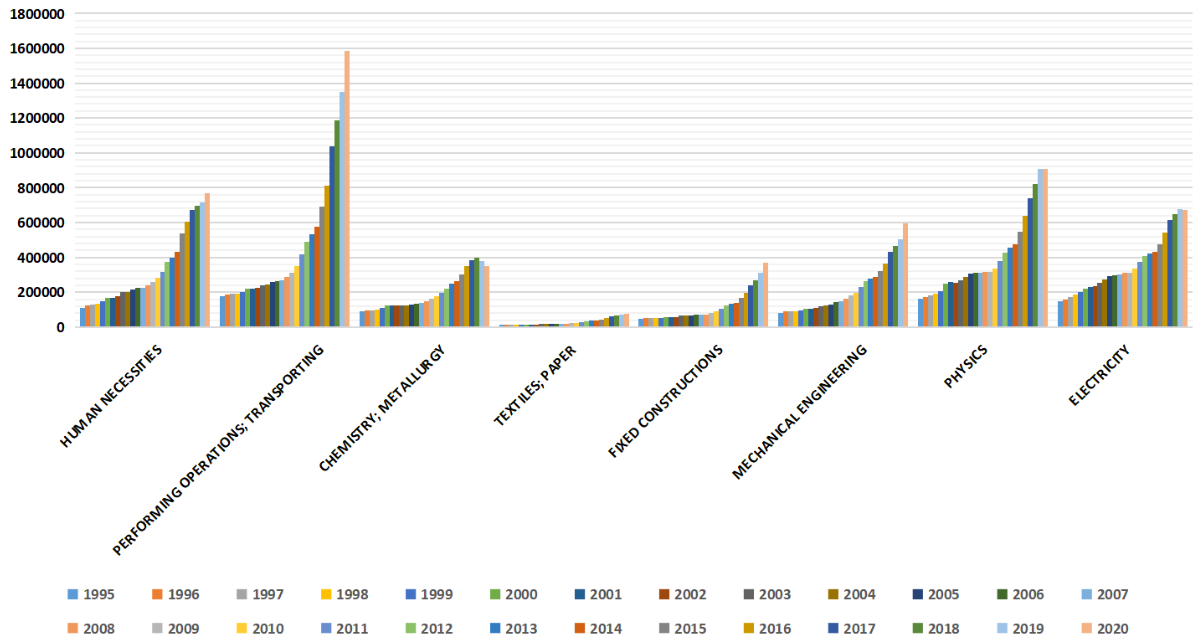
- Human necessities;
- Performing operations, transporting;
- Chemistry, metallurgy;
- Textiles, paper;
- Fixed construction;
- Mechanical engineering, lighting, heating, weapons, blasting;
- Physics;

[11]WIPO provides a full list of technology fields for invention applications. Each technology field has sub-classifications based on IPC codes.

- Electricity.

Figure 2.3 shows an increase in innovation across all technology fields. After 2000, the number of new inventions jumps considerably. Specifically, the performing operations and transportation field had the fastest growth rates (17% on average) and the highest number of inventions (1,585,947) in 2020, followed by physics (907,545), human necessities (766,265), and electricity (672,017).

Figure 2.3: Total inventions in each technology field.



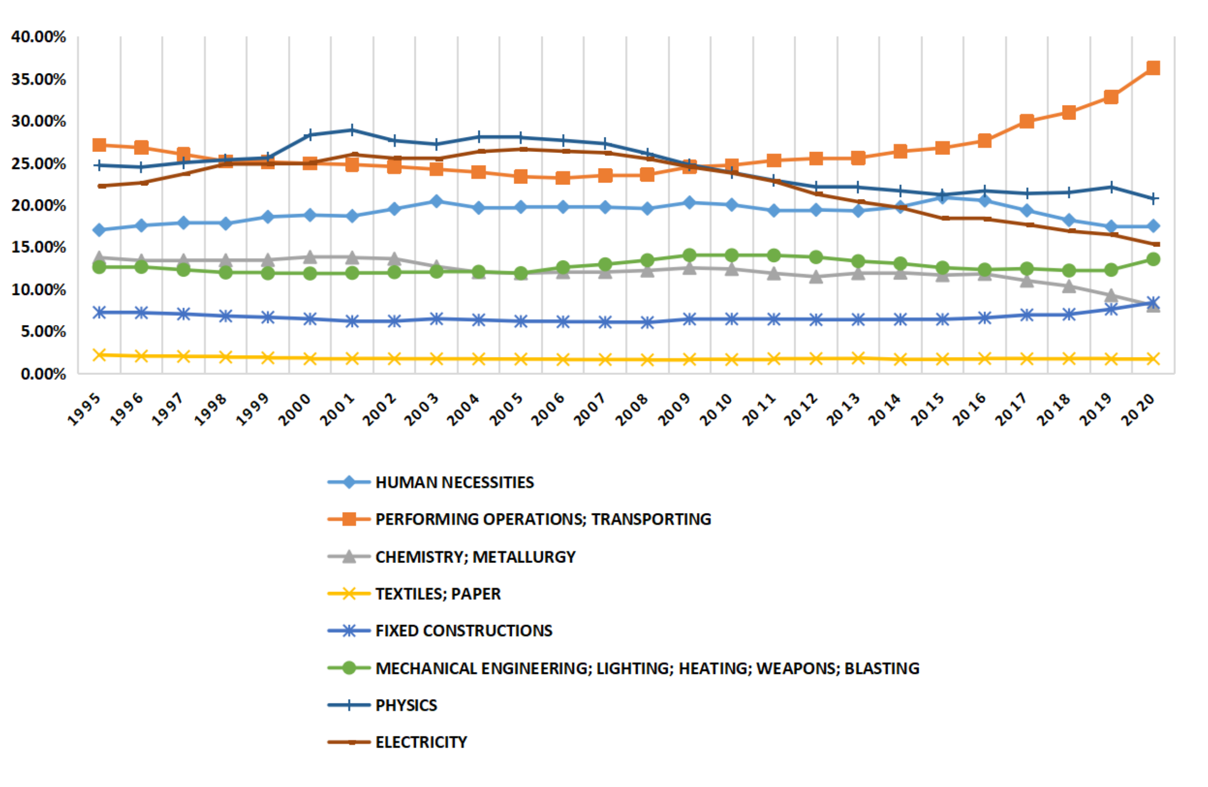
Source: Authors' own calculations based on PATSTAT data.

Although inventions overall have increased, in some technological fields, such as textiles, paper, and fixed construction, the number of inventions is fairly low. These trends reflect natural trends in innovation, with some industries being more likely to rely on existing technologies and to rely more on skilled workers than new technologies (Magee, 1997; Ogunrinde, Nnaji, and Amirkhanian, 2020).

Figure 2.4 presents the trend of inventions by technology field as a share of the total inventions. The percentage of inventions in the performing operations and transportation technology field is the largest, accounting for around 27% and 35% of inventions in 1995 and 2020, respectively. However, between 2000 and 2010, inventions related to physics accounted for the largest share, followed by inventions related to electricity, which demonstrates how innovation trends change over time. According to the WIPO classification, the physics category includes inventions related to information storage, computing, and communications. The electricity category includes inventions such as cables, electric communication technologies, and wireless communication technologies. These trends coincide with the move from the third to the fourth industrial revolution.[12] The third technological revolution was marked by the invention and application of atomic energy, electronic computers, space technology, biological engineering, and alternative energy (Prisecaru, 2016). In the late stage of the third technological revolution, the rapid development of microcomputers, wireless communications, and chip applications all marked a rapid increase in innovation related to physics and electricity. However, since 2010, the world has gradually moved towards the era of Industry 4.0, which is more about intelligent manufacturing. As explained by Bloem et al. (2014), Industry 4.0 was driven by new innovations in performing operations and transportation, such as 3D printing technology, autonomous driving technology, and the blockchain.

[12]The third industrial revolution began in the 1960s and is also called the computer or digital revolution (Schwab, 2017). Industry 4.0 was first proposed by Germany at the 2011 Hannover Fair and focuses on using cyber-physical systems, which involves digitising and intelligentising the whole production chain, including the upstream supply, manufacturing, and downstream sales. Industry 4.0 aims to achieve increasingly fast and effective supply chains (Prisecaru, 2016; Schwab, 2017).

Figure 2.4: Share of inventions from each technology field of the total number of inventions.



Source: Authors' own calculations based on PATSTAT data.

The next stage is to document where the innovation is taking place. Table 2.1 shows that the leading inventor economies and districts over the last 26 years (summed over 1995–2020) were the US, the Republic of Korea (KR), China (CN), Japan (JP), and Germany (GE). These economies have become innovation leaders not just due to their rapid economic development but also because of the development of a culture of R&D and strong government support for innovation.[13] Data released by WIPO show that in 2021, Chinese applicants filed 69,500 international patent applications through the Patent Cooperation Treaty (PCT), causing the People's Republic of China to rank first in the number of applications for the third consecutive year.

The US not only ranks first in terms of the GDP per capita but also consistently ranks first in

[13]Many studies have highlighted the role of culture and support in stimulating innovation (P. K. Wong, Ho, and Autio, 2005; Hall and Josh Lerner, 2010; J. Edler and Fagerberg, 2017).

terms of the innovation index. Meanwhile, Japan, the Republic of Korea, and Germany have a strong track record on electricity and transportation research. It is argued that the leading economies have a strong research infrastructure, including research organisations and universities. To encourage innovation, in addition to providing financial and policy support, education and enterprise innovation capabilities and a sound patent protection system should all be valued by governments (Maritz et al., 2014; Acemoglu and Akcigit, 2012).

Table 2.1: Top 20 inventor economies and districts globally in terms of technological innovation.

Rank	**Economy**	**% of total global inventions**
1	United States	7.39%
2	Republic of Korea	5.20%
3	China	5.16%
4	Japan	3.65%
5	Germany	2.97%
6	Taipei,China	2.24%
7	Russian Federation	0.89%
8	France	0.88%
9	United Kingdom	0.79%
10	Canada	0.55%
11	Italy	0.39%
12	Netherlands	0.37%
13	India	0.32%
14	Switzerland	0.32%
15	Spain	0.32%
16	Ukraine	0.29%
17	Sweden	0.25%
18	Poland	0.23%
19	Israel	0.21%
20	Finland	0.19%

Source: Authors' own calculations based on PATSTAT data.

Table 2.2 lists the top 20 inventor economies and districts for each technology field, considering the sum of total inventions between 1995 and 2020. The US, China, Japan, Germany, and the Republic of Korea are also the leading economies in each technology field. China replaced the US at the top in the paper industry; China and the Republic of Korea rank first and second in the fixed construction industry, while the US ranks third. In China, infrastructure construction and basic manufacturing are considered to have a significant 'multiplier effect', which means that investment in infrastructure construction is thought to create substantial social aggregate demand, national income, and jobs (Ansar et al., 2016). China's continued but slowing investment in construction continues to promote technological upgrading in this field and hence an increasing number of patents. Post-COVID, the Republic of Korea plans to invest $14.7 billion in infrastructure projects to stimulate economic recovery.

Since 2000, the scientific research capabilities of a number of Asian economies have improved significantly. In addition to Japan, the Republic of Korea, and China, India also appears on the list and performs most strongly in the chemical industry. Taking advantage of the economy's loose patent protection, low costs, and language benefits, Indian pharmaceutical companies actively develop patents, conduct standardised market certification, undertake international API transfer orders, and gradually sell preparations to developed economies (Grace, 2004). As early as 2007, Indian companies spent 30% of their total global investment in the generic drug industry, and R&D investment accounted for more than 10% of sales revenue (Greene, 2007).

Table 2.2: Top 20 inventor economies and districts globally in each technology field.

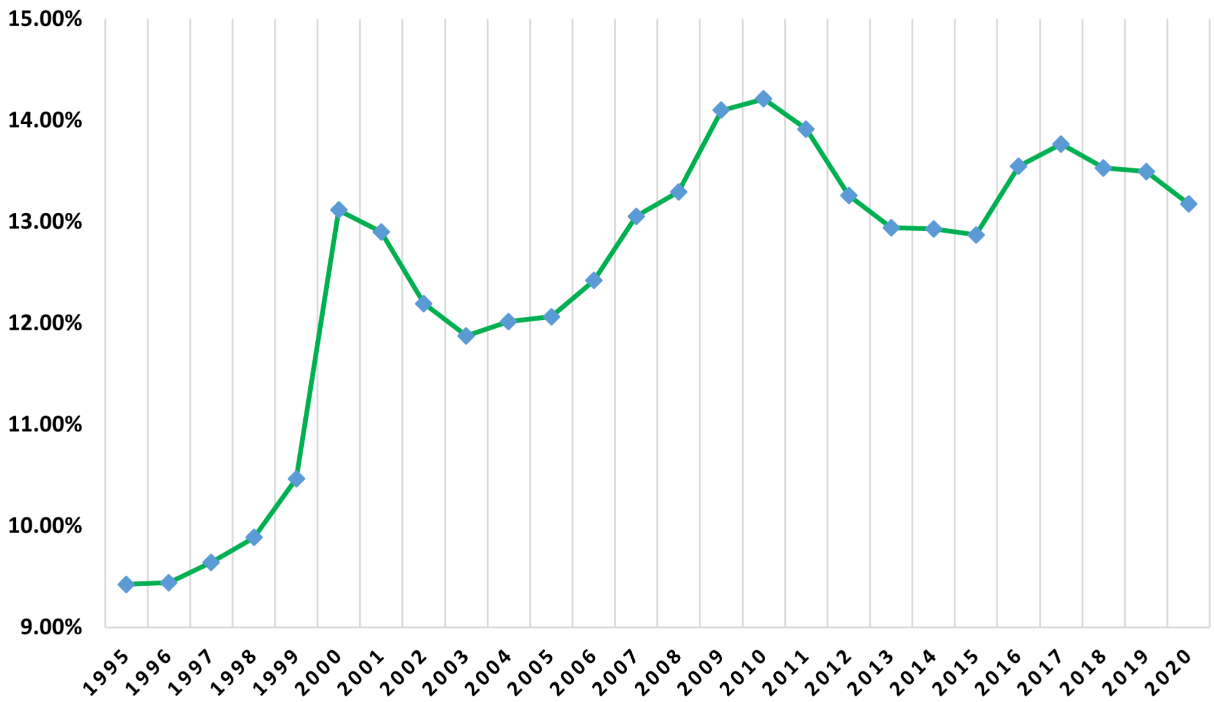
Rank	Human necessities	Transporting	Chemistry	Textiles, paper	Fixed construction	Mechanical engineering	Physics	Electricity
1	US	US	US	CN	CN	US	US	US
2	CN	KR	JP	KR	US	CN	JP	KR
3	KR	GE	CN	US	KR	GE	KR	JP
4	GE	CN	KR	GE	GE	KR	CN	CN
5	TW	JP	GE	JP	TW	JP	GE	TW
6	JP	TW	RU	TW	RU	TW	TW	GE
7	RU	FR	FR	IT	UK	FR	UK	FR
8	UK	UK	UK	FR	JP	RU	FR	UK
9	FR	RU	TW	FI	FR	UK	CA	CA
10	CA	IT	CA	UK	CA	IT	RU	IN
11	IT	CA	CL	CL	SP	CA	IN	RU
12	SP	SP	NL	TR	PL	SP	NL	NL
13	NL	CL	IN	SE	IT	AT	IL	SE
14	CL	NL	IT	CA	NL	PL	CL	FI
15	UA	SE	BE	RU	UA	NL	IT	IL
16	BR	PL	UA	NL	AT	CL	SE	IT
17	IL	UA	PL	AT	FI	UA	AU	CL
18	SE	AT	SP	BE	AU	SE	UA	AT
19	AU	BR	SE	SP	NO	TR	SP	SP
20	IN	FI	AU	CZ	CL	DEN	FI	SI

Source: Authors' own calculations based on PATSTAT data.
For a list of the abbreviations for economies used in this paper.

Having looked at the total inventions, we now turn to eco-innovation. Figure 2.5 presents the number of eco-innovations as a share of the total inventions between 1995 and 2020. The overall trend is that the number of eco-innovations is increasing, albeit with some peaks and troughs. For example, between 2000 and 2005, the number of total inventions increased significantly (by around 8% on average), while the number of eco-innovations remained relatively flat, leading to a significant drop in the share. However, after 2005 the upward trend resumed, perhaps driven by R&D investment that was initiated after the signing of the Kyoto Protocol, which was officially implemented in 2005. A key element of the Kyoto Protocol was for developed economies to reduce carbon emissions starting in 2005 and for developing economies to start reducing their emissions in 2013. In addition, the Kyoto Protocol recommends that governments adopt green development mechanisms to encourage developed and developing economies to work together to reduce greenhouse gas emissions collaboratively. Meanwhile, compared to Figure 2.2, although the quantity of non-eco innovations has significantly increased, their proportion of total innovations has slightly decreased. This is because the quantity of eco-innovations has fluctuated and risen since 1995.

A number of studies show that implementing the Kyoto Protocol positively stimulated eco-innovation, particularly in the area of renewable energy (Miyamoto and Takeuchi, 2019). It should be noted that 2012 marked the end of the first commitment period of the Kyoto Protocol. In 2015 the Kyoto Protocol was replaced by the Paris Agreement, which was signed by 178 economies (Schreurs, 2016). The Paris Agreement required economies to make an effort to reduce their emissions based on their promises one year later. This matches the uptick in the share of eco-innovations after 2016.

Figure 2.5: Share of eco-innovations of the total inventions.



Source: Authors' own calculations based on the PATSTAT database.

The next step is to present the equivalent of Figure 2.3 for eco-innovation. Hence, Figure 2.6 shows the total number of eco-innovations from 1995 to 2020 according to WIPO's 'IPC Green Inventory', which categorises ESTs into the following six green technology fields[14]:

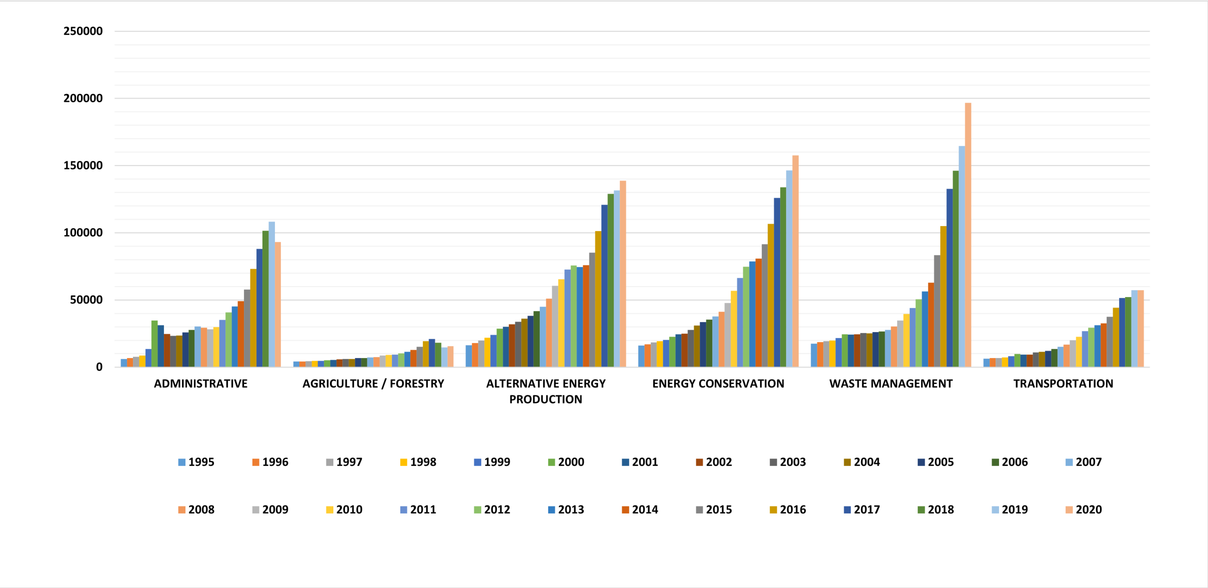
- Alternative energy production (e.g., technologies related to hydropower);
- Transportation (including inventions related to hybrid electric vehicles);
- Energy conservation (e.g., inventions used to store electrical energy);
- Waste management (e.g., technologies used for pollution control);
- Agriculture/Forestry (including alternative irrigation techniques and organic fertilisers derived from waste);

[14]Nuclear power generation (such as nuclear reactors or nuclear power plants) is excluded in our research, as it produces uranium waste (although it is zero carbon).

- Administrative, regulatory, or design aspects (technologies related to carbon/emission trading or teleworking equipment).

Figure 2.6 shows that there has been an increasing trend in eco-innovations in each green technology field. Except for agriculture/forestry, the number of inventions in each green technology field shows fairly rapid growth. For example, the total number of technologies (patent families) related to waste management rose from 17,546 to 196,687 between 1995 and 2020. Total eco-innovations from the waste management, energy conservation, and alternative energy production categories remained in the top three in 1995 and 2020, with little evidence of a slowdown during 2020 when the first lockdowns due to COVID were being implemented. Figure 2.6 also shows an increase, post-Paris Agreement, in investment to stimulate clean energy, renewable energy, and energy conservation research, and this may explain the rapid growth after 2016 in inventions related to waste management, energy conservation, and alternative energy production.

Figure 2.6: Total number of eco-innovations by green technology field.

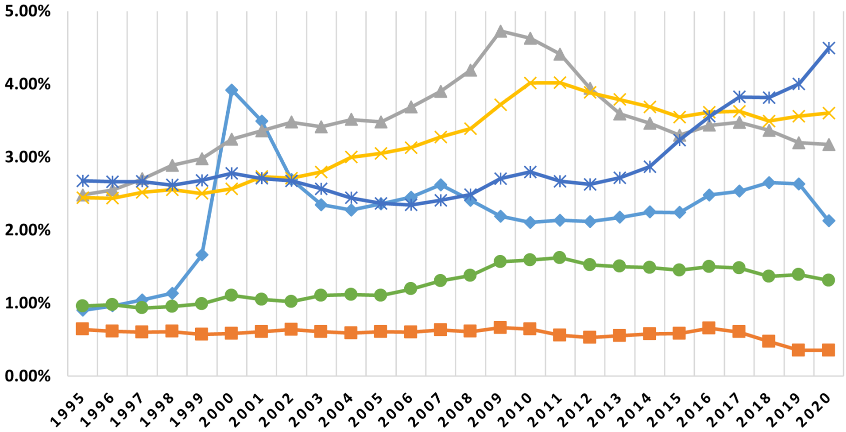


Source: Authors' own calculations based on PATSTAT data.

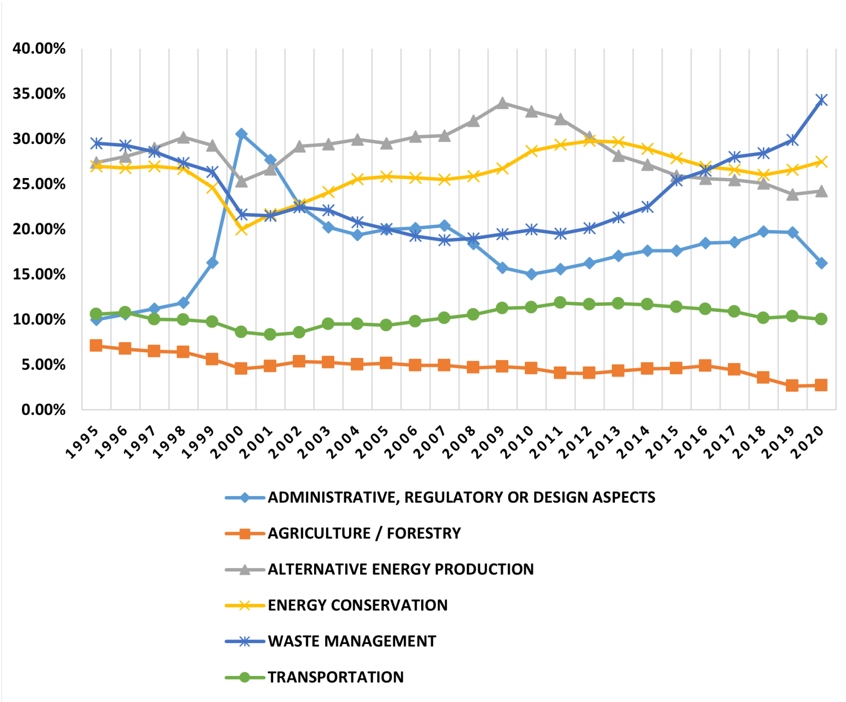
Figure 2.7 shows two different ways to represent the number of eco-innovations: (1) the number of inventions in each green technology field as a share of the total inventions (the total number of patents applied for in a given year), and (2) the number of inventions in each green technology field as a share of the total eco-innovations (the total number of eco-innovation patents applied for in a given year). Figure 2.7a shows that the share of eco-innovations of the total inventions is between 0.2% and 4%. The largest shares are in energy conservation, waste management, and alternative energy production.

Comparing sectors, in 2020, eco-innovations related to waste management were ranked first (4.8%), followed by energy conservation (3.6%) and alternative energy production (3.3%). Figure 2.7b presents the same information but as a share of the total eco-innovations and shows that eco-innovations related to waste management peaked at around 37% in 2020. Although the number of eco-innovations as a percentage of the total innovations remains limited, waste management, energy conservation, and alternative energy production remain the three most innovative green technology fields.

Figure 2.7: Share of eco-innovations from each technology field of the total inventions and total eco-innovations.



(a) Share of eco-innovations from each technology field of the total inventions



(b) Share of eco-innovations from each technology field of total eco-innovations

Source: Authors' own calculations based on PATSTAT data.

Table 2.3 lists the leading inventor economies and districts engaged in eco-innovation. The results are similar to those shown in Table 2.1, with the US, the Republic of Korea, Japan, China, and Germany being the top five inventor economies in terms of both total innovation and eco-innovation. The main difference is that the United Kingdom, France, and India are ranked higher for eco-innovation. China and India are the only developing economies with substantial CO_2 emissions that appear on the list.

As a developing economy with significant carbon emissions, China has launched more than 20 critical projects that relate to carbon-neutral technologies such as hydrogen energy and new-energy vehicles (Y. Wang and Liang, 2013). For example, coal consumption using ultra-supercritical power generation technologies has dropped to 266.8 g/kWh, which is 11% lower than the average coal consumption of traditional thermal power units. To support its transport and energy-intensive industrial sectors, India has also introduced several policies to encourage the adoption of green technologies, including the implementation of strict emission standards to regulate air pollutant emissions from compression ignition engines, a battery replacement policy, and appliance energy-efficiency standards (Tibrewal and Venkataraman, 2021). The Indian electric vehicle market is growing steadily, with a compound annual growth rate of 42.8%, and is one example of how environmental policies can stimulate eco-innovation and promote the development of new industries (Brar et al., 2021).

As before, we now describe the top 20 inventor economies and districts for each green technology field based on the total number of eco-innovations between 1995 and 2020. Table 2.4 shows that since 2000, the scientific research capabilities of a number of Asian economies have improved significantly. The US, the Republic of Korea, Japan, Germany, and China are the leading economies in each green technology field. The Republic of Korea has the top position in the waste management category. In addition to Japan, the Republic of Korea, and China, India and Taipei,China also specialise in a large number of green technology fields.

Table 2.3: Top 20 inventor economies and districts globally in terms of eco-technological innovation.

Rank	Economy	% of total global eco-innovations
1	United States	8.96%
2	Republic of Korea	6.18%
3	Japan	4.22%
4	China	3.86%
5	Germany	3.34%
6	Taipei,China	1.79%
7	France	0.98%
8	United Kingdom	0.87%
9	Russian Federation	0.73%
10	Canada	0.72%
11	Netherlands	0.47%
12	India	0.39%
13	Italy	0.31%
14	Switzerland	0.31%
15	Spain	0.29%
16	Poland	0.27%
17	Australia	0.24%
18	Ukraine	0.24%
19	Austria	0.23%
20	Sweden	0.22%

Source: Authors' own calculations based on PATSTAT data.

Table 2.4: Top 20 inventor economies and districts globally in each green technology field.

Rank	Administrative	Agriculture	Alternative energy	Energy conservation	Waste management	Transportation
1	US	US	US	US	KR	US
2	KR	CN	KR	KR	US	JP
3	JP	GE	JP	JP	CN	GE
4	CN	KR	CN	CN	GE	CN
5	GE	JP	GE	GE	JP	KR
6	TW	UK	TW	TW	TW	TW
7	UK	FR	FR	FR	RU	FR
8	CA	RU	UK	UK	FR	RU
9	IN	CL	NL	CA	UK	UK
10	FR	CA	CA	RU	CA	CA
11	IL	IN	RU	NL	PL	IT
12	AU	SP	DEN	CL	NL	AT
13	NL	TW	SP	AT	UA	CL
14	CL	BR	IT	IT	SP	SE
15	SE	IT	CL	PL	IT	PL
16	RU	UA	PL	IN	BR	UA
17	FI	PL	IN	SP	FI	SP
18	IT	AU	UA	SE	SE	NL
19	SI	IL	AU	FI	CZ	CZ
20	BR	BE	BE	IL	CL	IN

Source: Authors' own calculations based on PATSTAT data.

Tables 2.5 and 2.6 show the performance of the top 20 inventor economies or economies based on different technology classifications. To assess the inventor economies' specialisation in a certain technology field, we measure a economy's 'relative technological advantage' (RTA) (Haščič and Migotto, 2015a). The RTA is calculated as follows:

$$RTA_{ij} = (IN_{ij}/IN_{wj})/(TI_i/TI_w), \tag{2.1}$$

where RTA_{ij} is the RTA of economy i in technology field j; IN_{ij} is the total number of inventions of economy i in technology field j; IN_{wj} is the total number of inventions globally in technology field j; TI_i is the total number of inventions of economy i; and TI_w is the total number of inventions globally. An RTA larger than one means that the economy has a prominent position in that technology field. A higher RTA implies that the economy is more specialised in that specific technology field compared to other technology fields.

Table 2.5 shows the RTAs of the top 20 inventor economies or economies based on the total number of inventions (eco-innovations and non-eco-innovations). Based on the WIPO classification, we classify technologies into eight different fields. Table 2.5 shows that the US specialises in inventions related to physics (1.62), electricity (1.36), chemistry (1.32), and human necessities (1.33). Economies such as the Republic of Korea, Japan, China, and India have a significant specialisation in electricity-related technologies. Germany specialises in mechanical engineering and weapons manufacturing, while the United Kingdom is stronger in chemistry.

Turning to eco-innovation, Table 2.6 presents the RTAs for the top 20 inventor economies or economies based on eco-innovations. Recall that the WIPO Green Inventory Scheme classifies green technologies into seven different green technology fields. Table 2.6 shows that the US and the Republic of Korea have a specialisation in administrative, regulatory, or design eco-innovations, and they do not produce as many eco-innovations related to agriculture. Germany and Austria specialise in green transportation technologies, while Japan, France, Spain, the Netherlands, and Sweden all have a relative specialisation in alternative energy. The United Kingdom, Spain, Italy, and Poland tend to specialise in eco-innovations related to agriculture and forestry.

The results presented in Tables 2.5 and 2.6 show that India has its most significant relative advantage in the administrative, regulatory, or design category. Switzerland has a high RTA for agriculture-related technologies. Although the Netherlands scores most highly for alternative energy production, Taipei,China has the highest RTA for energy conservation-related innovation.

Table 2.5: RTAs of the top 20 inventor economies and districts based on the WIPO classification.

Inventor economy	Human necessities	Transporting	Chemistry	Textiles, paper	Fixed construction	Mechanical engineering	Physics	Electricity
US	1.33	0.72	1.32	0.61	0.65	0.76	1.62	1.36
KR	0.83	0.73	0.91	1.02	0.91	0.86	1.12	1.56
CN	1.11	0.70	0.94	1.03	0.94	1.03	0.87	1.14
JP	0.56	0.93	1.50	0.74	0.23	0.90	1.73	2.00
GE	0.84	1.27	1.18	1.36	0.86	1.70	0.98	1.03
TW	1.02	0.76	0.41	0.64	0.68	0.86	1.11	1.50
RU	1.58	0.66	1.73	0.36	1.10	0.96	0.79	0.49
FR	1.19	1.09	1.52	0.85	0.88	1.31	1.08	1.14
UK	1.42	0.78	1.58	0.78	1.13	0.95	1.31	1.13
CA	1.31	0.79	1.38	0.58	1.26	0.83	1.43	1.32
IT	1.43	1.14	1.26	2.27	1.03	1.24	0.72	0.74
NL	1.49	0.77	1.60	0.87	0.93	0.77	1.23	1.19
IN	0.88	0.37	1.70	0.45	0.19	0.47	1.83	1.72
CL	1.66	0.93	1.87	1.85	0.73	0.85	1.17	0.86
SP	1.75	1.01	1.11	0.89	1.62	0.94	0.68	0.58
UA	1.76	0.69	1.38	0.52	0.97	0.92	0.76	0.38
SE	1.15	0.91	1.15	1.47	0.71	0.99	1.04	1.70
PL	1.09	0.96	1.74	0.77	2.13	1.24	0.67	0.55
IL	1.52	0.43	1.04	0.30	0.28	0.37	2.07	1.53
FI	0.79	0.81	0.96	3.62	1.25	0.86	1.05	1.70

Source: Authors' own calculations based on PATSTAT data.

Table 2.6: RTAs of the top 20 inventor economies and districts based on the WIPO Green Inventory List.

Inventor economy	Administrative	Agriculture	Alternative energy	Energy conservation	Waste management	Transportation
US	1.91	1.47	1.03	0.76	0.48	0.73
KR	1.66	0.55	0.92	1.00	0.72	0.79
JP	0.93	0.71	1.21	1.27	0.47	1.36
CN	0.61	1.40	1.06	1.01	0.97	1.34
GE	0.70	1.42	1.10	1.07	0.68	1.62
TW	1.11	0.32	0.94	1.40	0.44	1.37
FR	0.81	1.77	1.21	0.88	0.76	1.25
UK	1.29	2.02	1.15	0.81	0.67	0.77
RU	0.33	2.04	1.06	0.70	1.09	1.23
CA	1.54	1.31	1.15	0.74	0.72	0.83
NL	0.55	0.88	1.80	0.86	0.63	0.51
IN	2.60	2.11	0.77	0.58	0.41	0.46
IT	0.65	1.72	1.20	0.82	0.86	1.50
CL	0.79	3.81	1.08	0.95	0.55	1.04
SP	0.63	2.07	1.36	0.76	0.94	0.94
PL	0.32	1.86	1.24	0.87	1.33	1.06
AU	1.73	1.90	1.18	0.59	0.66	0.61
UA	0.29	2.22	1.20	0.67	1.23	1.20
AT	0.48	1.17	1.01	1.17	0.73	2.03
SE	1.10	1.08	0.93	0.92	0.83	1.36

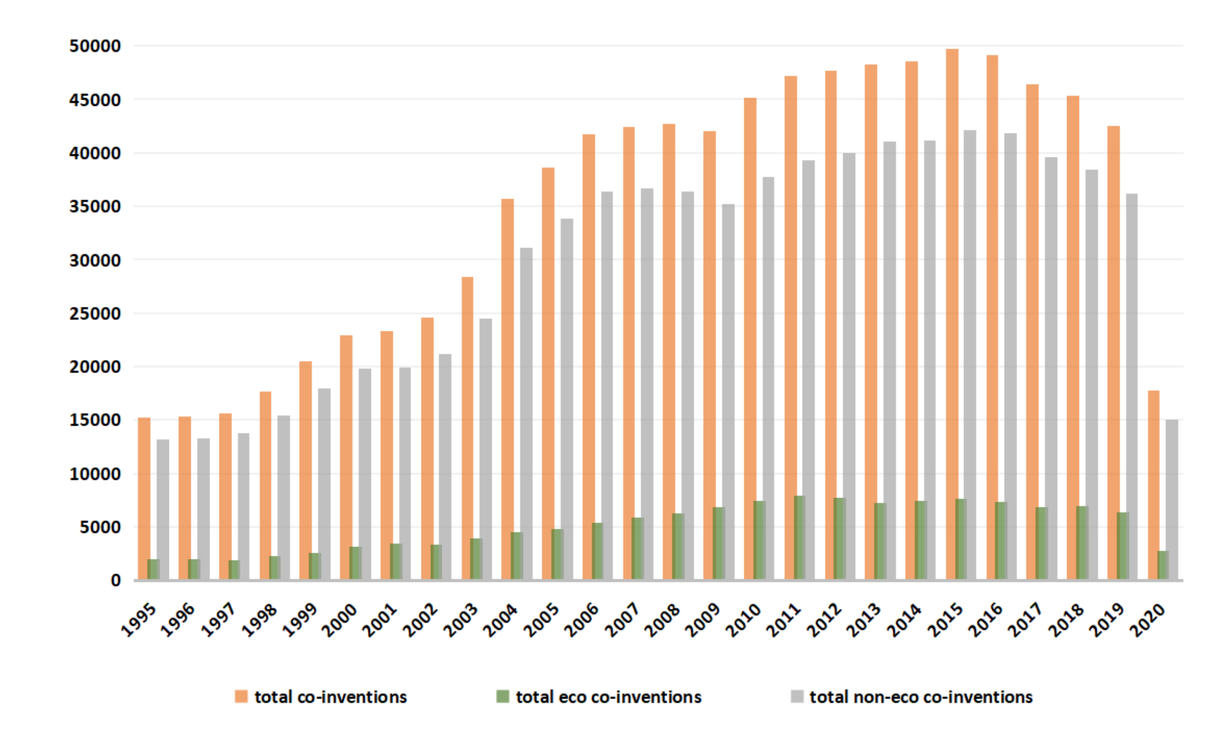
Source: Authors' own calculations based on PATSTAT data.

2.4 Trends in international technological collaboration

International technological collaboration, also called international collaborative innovation or international collaborative innovation, refers to inventions for which at least two inventors reside in different economies. To count the number of international collaborative innovations, we calculate the total number of simple patent families. Trends in international collaborative innovations, international collaborative eco-innovations, and international collaborative non-eco-innovations from 1995 to 2020 are presented in Figure 2.8.

An immediate observation is that there has been a significant increase in the number of international collaborative innovations and international collaborative non-eco-innovations since 1995. Although there was a dip in the total inventions in 2009 following the global financial crisis, the number of international collaborative eco-innovations continued to rise slightly and peaked at 7,885 in 2011. The total number of collaborative innovations peaked at 49,761 in 2015, when the number of collaborative non-eco-innovations was 42,138. Since 2015 the number of collaborative eco-innovations has remained fairly stable but may have dipped slightly, following the pattern for total collaborative innovations. In these data we see a significant shock to collaborative innovation driven by the COVID pandemic.

Figure 2.8: International collaborative innovations, collaborative eco-innovations, and collaborative non-eco-innovations.

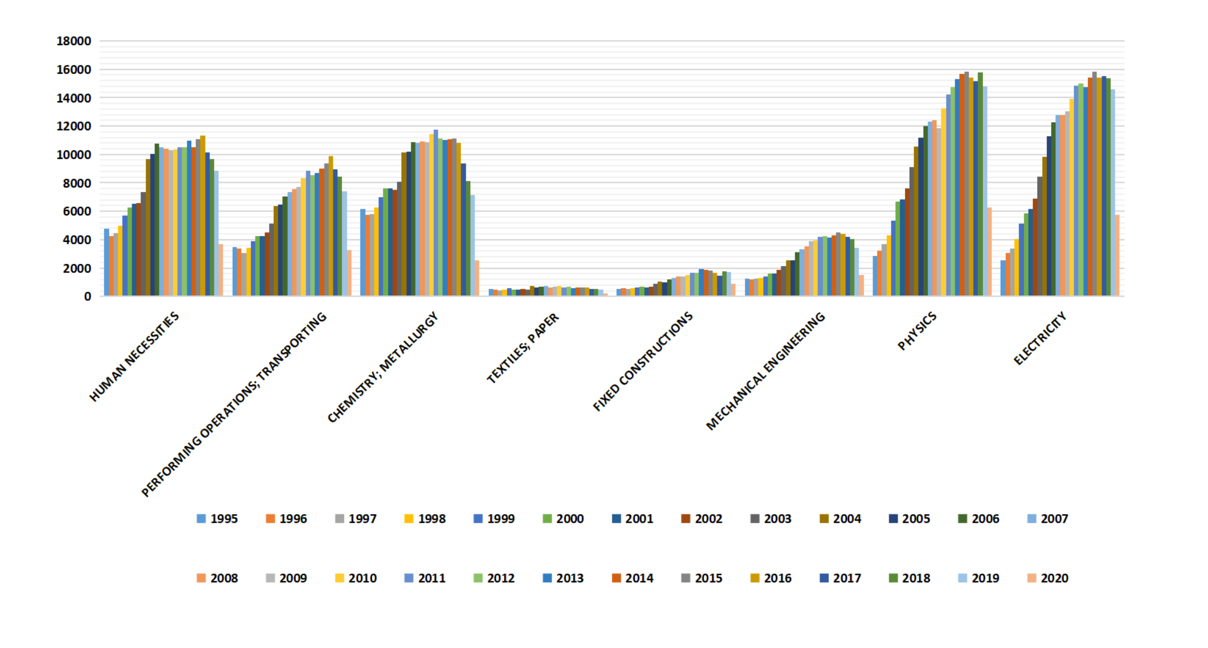


Source: Authors' own calculations based on PATSTAT data.

Figure 2.9 shows the development of international collaborative innovations at a more disaggregated level. In all technical fields, the number of cooperative inventions has increased. Moreover, from 1995 to 2019 there has been a significant increase in collaborative innovations related to physics and electricity (which increased from 2,863 to 14,799 and 2,526 to 14,562, respectively). As shown in Figure 2.9, there was a significant drop in 2020 due to COVID.

During this period more and more economies increased their investment in high-tech R&D. International research collaboration can amplify the effects of domestic research capabilities, increase invention efficiency, and lead to greater technology transfer (Andrade, Los Reyes Lopez, and Martín, 2009). The main growth areas since 2000 have been technologies related to physics and electricity, which include computers and wireless communications (Yamin, 2019).

Figure 2.9: Total international collaborative innovations in each technology field.



Source: Authors' own calculations based on PATSTAT data.

Table 2.7 shows the top 20 inventor economy pairs in terms of international collaborative innovations. The top 20 economy pairs include a wide range of economies, including the US, Germany, Japan, India, Canada, France, the Republic of Korea, and China. These economies tend to have strong research capabilities and stable economic environments. According to the table, over our time period, cooperation between China and the US was responsible for the largest number of inventions, with 6.43% of the world's total international collaborative innovations, followed by collaboration between Canada and the US (5.65%), India and the US (5.60%), and Germany and the US (5.58%). Cooperation between economies is influenced by many factors, such as culture, language, geographic location, and politics (Dawes, Gharawi, and Burke, 2012). The United States and Canada are neighbouring economies and Canada is also the US's largest trading partner (Wonnacott and Williamson, 1987). Geographical proximity and trade are likely to be significant contributors to a greater degree of cooperative innovation between the two economies. Aside from Canada, the two most important innovation partners for the US are China and India. Perhaps unsurprisingly, the US is the most important innovation partner for many economies on the list. In Europe, Germany, the United Kingdom, and France collaborate most with the US, and in Asia, China, India, Japan, and the Republic of Korea collaborate most with the US.

Table 2.8 shows the most important inventor economy pairs by technology field. The US is consistently one of the top co-inventors across all technology fields. The cooperation between the US and China in chemistry and electricity ranks first, while the US is the leading innovation partner for Germany in technologies related to transportation, engineering, and paper. The United Kingdom and the US generate the largest number of collaborative innovations in the human necessities and fixed construction fields. For physics, India has the largest number of collaborative innovations with the US.

Table 2.7: Top 20 inventor economy pairs globally in terms of total international collaborative innovations.

Rank	Economy	% of total global collaborative innovations
1	US-CN	6.43%
2	US-CA	5.65%
3	IN-US	5.60%
4	GE-US	5.58%
5	UK-US	5.24%
6	TW-CN	2.99%
7	JP-US	2.80%
8	FR-US	2.71%
9	GE-CL	2.44%
10	US-KR	2.27%
11	FR-GE	2.12%
12	US-TW	1.93%
13	US-IL	1.67%
14	AT-GE	1.66%
15	US-CL	1.44%
16	US-NL	1.41%
17	UK-GE	1.39%
18	NL-GE	1.26%
19	FR-CL	1.15%
20	CN-KR	1.03%

Source: Authors' own calculations based on PATSTAT data.

Table 2.8: Top 20 inventor economy pairs globally in each technological field.

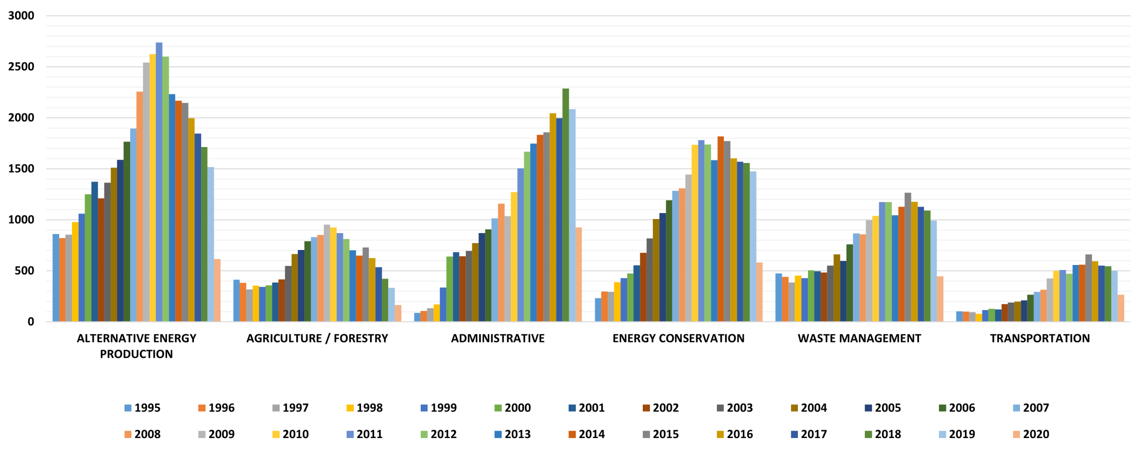
Rank	Human necessities	Transporting	Chemistry	Textiles, paper	Fixed construction	Mechanical engineering	Physics	Electricity
1	UK-US	US-GE	CN-US	GE-US	UK-US	US-GE	US-IN	CN-US
2	GE-US	US-CA	GE-US	GE-CL	US-CA	GE-FR	CA-US	IN-US
3	CA-US	UK-US	US-UK	US-UK	US-GE	CA-US	UK-US	US-CA
4	US-CN	CN-US	CA-US	AT-GE	US-FR	IN-US	US-CN	TW-CN
5	GE-CL	GE-CL	US-IN	CA-US	US-CN	UK-US	US-GE	GE-US
6	US-FR	FR-GE	US-FR	US-CN	AT-GE	AT-GE	TW-CN	UK-US
7	US-IN	US-IN	GE-CL	GE-FR	IN-US	CL-GE	JP-US	US-KR
8	FR-GE	JP-US	US-JP	FR-US	US-NL	CN-TW	US-IL	JP-US
9	JP-US	AT-GE	FR-GE	BE-US	GE-CL	US-CN	US-FR	US-TW
10	CL-US	FR-US	UK-GE	GE-UK	US-NO	NL-GE	US-KR	US-FR
11	FR-CL	CN-TW	KR-US	FR-CL	GE-FR	US-FR	TW-US	US-IL
12	UK-GE	GE-NL	US-NL	IN-US	AU-US	GE-UK	GE-CL	JP-KR
13	KR-US	UK-GE	FR-CL	NL-US	FR-UK	US-JP	CL-US	JP-CN
14	NL-US	KR-US	CL-US	NL-GE	CN-TW	GE-IT	NL-US	CN-KR
15	US-IL	US-NL	US-BE	US-JP	JP-US	TW-US	US-AU	GE-AT
16	FR-UK	US-TW	GE-AT	US-CL	US-SI	US-IT	FR-GE	IN-CN
17	US-IT	GE-BE	NL-GE	KR-US	RU-UA	GE-BE	IRL-US	FR-GE
18	AU-US	US-BE	FR-UK	US-FI	RU-US	US-KR	GE-AT	GE-CL
19	TW-US	US-CL	GE-BE	IT-GE	GE-UK	CN-GE	NL-GE	NL-US
20	GE-NL	CL-FR	FR-BE	JP-KR	NO-UK	JP-KR	UK-GE	US-SE

Source: Authors' own calculations based on PATSTAT data.

Figure 2.10 presents the development of international collaborative eco-innovations in each green technology field. There is a significant increase in collaborative eco-innovation in each green technology field. Despite the limited extent of the collaborative innovation in alternative energy, it has proven to be one of the most promising future clean energy sources for humanity. We can also note that collaborative innovation in alternative energy, energy conservation, and waste management is growing rapidly, reflecting the trend of more and more economies investing in green technology-related R&D and seeking solutions to environmental problems through cooperation.

Despite the increases in collaborative eco-innovation, Figure 2.10 also shows how the number of collaborative innovations fell over the last 5 years or so of the sample, with notable declines in alternative energy production and agriculture and forestry. Given that cooperation is seen as an important way that green technologies are diffused globally, these declines are potentially important and warrant further investigation.

Figure 2.10: Total international collaborative eco-innovations in each technology field.



Source: Authors' own calculations based on PATSTAT data.

Turning again to collaborative eco-innovations, Table 2.9 presents the most important eco-inventor economy pairs at the economy level. Although China and the US rank first in collaborative innovation, they only rank fifth when it comes to collaborative eco-innovation, with first place now taken by the US and Canada, whose collaborative eco-innovations account for 6.29% of the total international collaborative eco-innovations. In addition, the US and Germany, as well as the US and the United Kingdom, rank relatively highly for collaborative eco-innovations. China and India are the only developing economies that make the list.

Table 2.9: Top 20 inventor pairs globally in terms of total collaborative eco-innovations.

Rank	Economy	% of total global collaborative eco-innovations
1	CA-US	6.29%
2	GE-US	6.13%
3	UK-US	5.97%
4	IN-US	5.50%
5	CN-US	5.05%
6	FR-US	2.66%
7	US-JP	2.50%
8	GE-FR	2.37%
9	GE-CL	2.28%
10	KR-US	2.07%
11	CN-TW	1.84%
12	AT-GE	1.83%
13	UK-GE	1.61%
14	NL-GE	1.53%
15	NL-US	1.47%
16	IL-US	1.41%
17	TW-US	1.36%
18	US-CL	1.35%
19	US-AU	1.22%
20	KR-JP	1.19%

Source: Authors' own calculations based on PATSTAT data.

Table 2.10 shows the most important inventor economy pairs for each green technology field. Again, the US is the most important eco-innovation partner for each green technology field. Cooperation between the US and China in energy conservation is still at the top of the list. The US is Germany's most important innovation partner in the agriculture field, while the United Kingdom and the US cooperate in innovation related to waste management. India and the US are ranked first in the administrative or design technology field.

Table 2.10: Top 20 inventor economy pairs in each green technological field.

Rank	Administrative	Agriculture	Alternative energy	Energy conservation	Waste management	Transportation
1	IN-US	US-GE	GE-US	CN-US	UK-US	CA-US
2	UK-US	FR-GE	US-CA	US-GE	US-CA	GE-AT
3	US-CA	US- UK	US-CN	CA-US	GE-US	US-GE
4	GE-US	GE-UK	US-UK	IN-US	US-CN	CN-US
5	US-CN	US-CN	US-IN	UK-US	US-IN	GE-CL
6	US-IL	GE-CL	JP-US	CN-TW	US-FR	US-IN
7	FR-US	CA-US	FR-US	KR-US	NL-GE	UK-US
8	US-IRL	FR-US	KR-US	JP-US	CL-GE	GE-FR
9	US-AU	US-IN	CL-GE	TW-US	GE-AT	TW-US
10	JP-US	CL-FR	NL-US	KR-JP	US-NL	CN-TW
11	TW-CN	US-CL	TW-CN	US-FR	FR-GE	US-JP
12	US-CL	US-JP	FR-GE	AT-GE	KR-US	US-KR
13	KR-US	GE-JP	NL-GE	GE-CL	JP-US	UK-GE
14	US-SI	UK-CL	GE-AT	GE-FR	BE-GE	US-FR
15	US-NL	FR-UK	TW-US	GE-NL	UK-GE	GE-NL
16	CL-GE	GE-SP	UK-GE	IL-US	BE-FR	CL-US
17	CA-UK	GE-SP	KR-JP	GE-UK	RU-US	UA-RU
18	UK-GE	AT-GE	AU-US	US-CL	KR-JP	JP-KR
19	US-BR	IN-GE	US-BE	NL-US	US-AU	SE-GE
20	IN-GE	BE-US	CL-US	CN-GE	US-BE	CN-GE

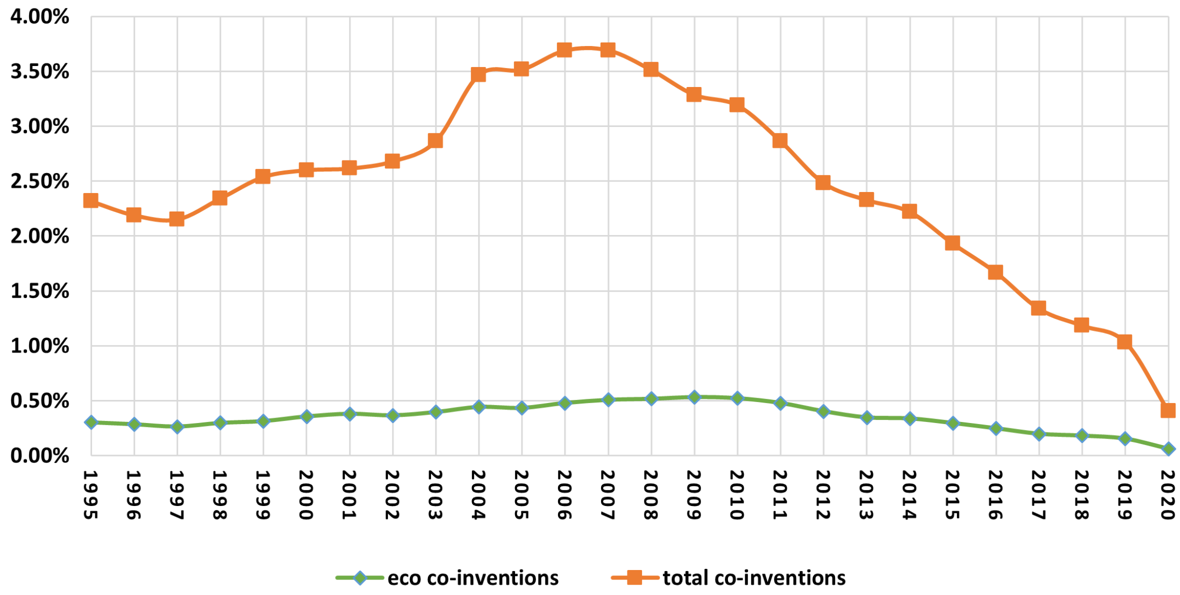
Source: Authors' own calculations based on PATSTAT data.

To show the evolution of collaborative innovation and collaborative eco-innovation, Figure 2.11 introduces the share of international collaborative innovations and the share of international collaborative eco-innovations of the total inventions between 1995 and 2020. Although the number of international collaborative innovations has significantly increased since 1995, the share of international collaborative innovations of the total inventions started to fall significantly after a peak of around 3.7% in 2007. The trend is similar for collaborative eco-innovations, but at a lower level; it is the more stable of the two trends.

A possible explanation is that since the beginning of the 21st century, economies have continued to build their domestic R&D capacity, which means that economies are increasingly able to support all of the different aspects of the innovation process without the need for help from overseas. It has been argued, as is central to the climate change debate, that eco-innovation is more complex and therefore requires skills and knowledge that are still beyond the capacity of individual economies to provide (M. Wagner and Llerena, 2011). Again, the final year of our sample shows a significant COVID effect, which not surprisingly impacts collaborative innovation even more heavily than innovation more generally.

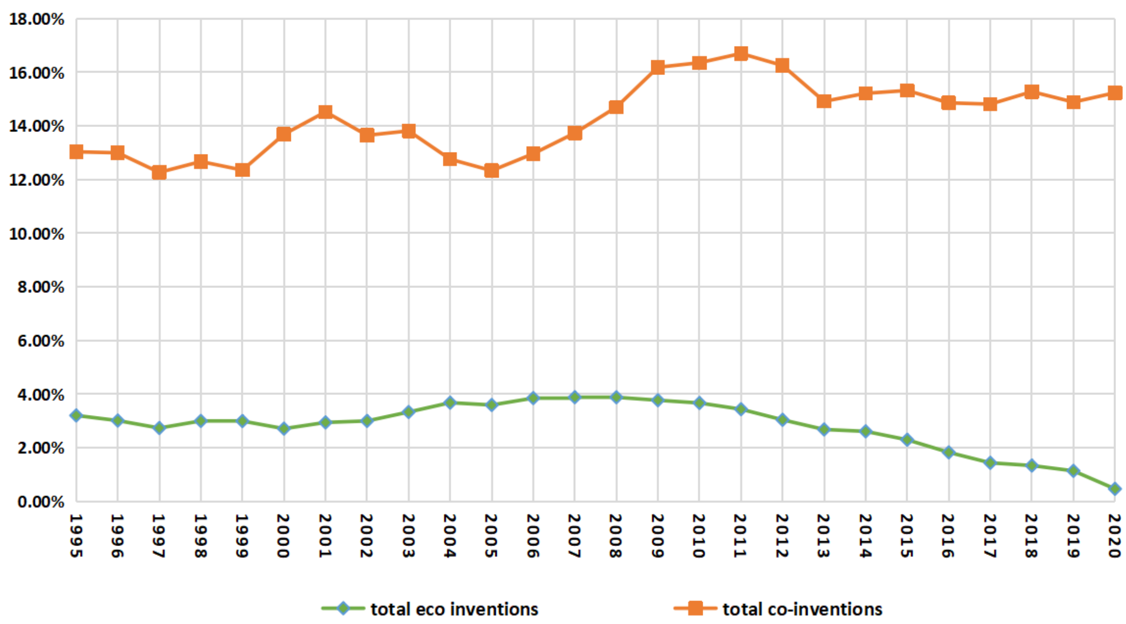
Figure 2.12 shows the share of total collaborative eco-innovations of the total eco-innovations and total collaborative innovations. The figure shows an upward trend in collaborative innovations but captures the fall in the share of collaborative eco-innovations after 2007 that we saw earlier. Although the total number of eco-innovations continues to increase, the share of collaborative eco-innovations of the total eco-innovations remains low and has fallen since the financial crisis. Understanding the reasons for these trends is an important area for future research.

Figure 2.11: Share of collaborative innovations and collaborative eco-innovations of the total inventions.



Source: Authors' own calculations based on PATSTAT data.

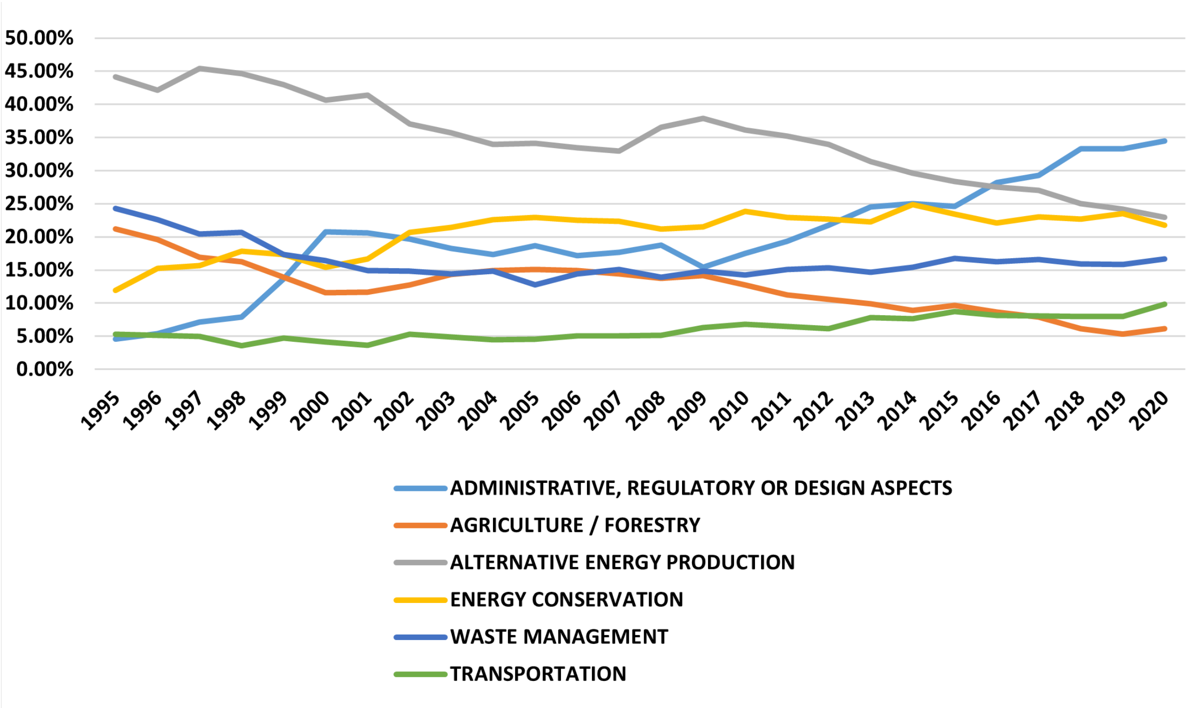
Figure 2.12: Share of total collaborative eco-innovations of the total eco-innovations and total collaborative innovations.



Source: Authors' own calculations based on PATSTAT data.

The next stage is to look at trends in collaborative eco-innovations at a more disaggregated level. Figure 2.13 presents the share of collaborative eco-innovations for each technology field of the total collaborative eco-innovations. Although collaborative eco-innovation shows a fairly continuous decline in alternative energy production-related green technologies and agriculture-related green technologies, the other trends show a slight increase. Hence, the overall decline we saw in Figures 2.12 and 2.13 appears to be driven by declines in the alternative energy production category.

Figure 2.13: Share of collaborative eco-innovations for each green technology field of the total international collaborative eco-innovations.



Source: Authors' own calculations based on PATSTAT data.

Tables 2.11 and 2.12 show the performance of the top 20 economy pairs in terms of collaborative innovations in different technology fields for both total collaborative innovations and total collaborative eco-innovations, respectively. Again, to assess the inventor economy pairs' specialisation in a specific technology field, we calculate the 'relative technological advantage' (RTA) (Haščič and Migotto, 2015a). As a reminder, the RTA is calculated as follows:

$$RTA_{ijk} = (COIN_{ijk}/COIN_{wj})/(TCOIN_{ij}/TCOIN_{w}), \tag{2.2}$$

where RTA_{ijk} is the RTA of the economy pair ij in the specific technology field k; $COIN_{ijk}$ is the total number of collaborative innovations of the economy pair ij in the specific technology field k; $TCOIN_{wk}$ is the total number of collaborative innovations globally in technology field k; $TCOIN_{ij}$ is the total number of collaborative innovations of the economy pair ij; and $TCOIN_{w}$ is the total collaborative innovations globally. Again, an RTA larger than one means that the economy pair is more specialised in that technology field. A higher RTA implies that the economy pair is more specialised in that specific technology field compared to other technology fields.

According to Table 2.11, Canada and the US tend to specialise in collaborative innovation related to fixed construction and physics technologies. The US and China have an RTA in electricity and chemistry-related technologies. According to Table 2.12, the US and Japan have an RTA in inventions related to alternative energy. It is also interesting to note that Germany and Switzerland have a strong collaborative eco-innovation RTA in agriculture-related technologies, while Germany and the Netherlands have an advantage in alternative energy collaborative innovation.

Table 2.11: Specialisation in each technology field (based on the WIPO classification) of the top 20 inventor pairs (the RTA is constructed based on the total collaborative innovations).

Inventor-pairs	Human necessities	Transporting	Chemistry	Textiles, paper	Fixed construction	Mechanical engineering	Physics	Electricity
US-CN	0.87	0.62	1.09	0.48	0.37	0.49	0.95	1.53
US-CA	1.01	0.89	0.92	0.72	1.26	0.81	1.26	1.07
US-IN	0.54	0.49	0.68	0.32	0.35	0.72	1.47	1.47
GE-US	1.13	1.15	1.19	1.21	0.63	1.08	1.06	0.85
US-UK	1.21	0.78	1.13	0.89	1.43	0.76	1.26	0.88
CN-TW	0.24	0.58	0.25	0.17	0.42	1.09	1.38	1.69
US-JP	0.88	0.97	1.17	0.53	0.45	0.63	1.21	1.26
US-FR	1.23	0.91	1.29	0.95	1.29	0.74	1.04	0.91
GE-CL	1.43	1.31	1.41	2.09	0.74	1.44	0.75	0.51
KR-US	0.69	0.66	0.88	0.59	0.31	0.43	0.97	1.66
FR-GE	1.21	1.35	1.40	1.27	0.70	2.22	0.64	0.63
US-TW	0.66	0.66	0.54	0.30	0.37	0.58	1.09	1.79
US-IL	0.85	0.38	0.41	0.26	0.14	0.18	1.88	1.31
GE-AT	0.73	1.49	0.91	2.51	1.21	2.23	0.66	0.98
CL-US	1.63	0.78	1.31	1.02	0.34	0.48	1.14	0.74
US-NL	1.10	1.05	1.40	1.27	1.31	0.60	1.03	0.86
UK-GE	1.50	1.10	1.50	1.57	0.62	1.28	0.75	0.67
NL-GE	0.98	1.23	1.19	1.36	0.67	1.91	0.84	0.83
FR-CL	1.97	0.89	1.68	1.82	0.34	0.61	0.89	0.48
KR-CN	0.72	0.51	0.86	0.56	0.21	0.29	0.85	1.62

Source: Authors' own calculations based on PATSTAT data.

Table 2.12: Specialisation in each green technology field (based on the WIPO Green Inventory List) of the top 20 inventor pairs (the RTA is constructed based on the total collaborative eco-innovations).

Inventor-pairs	Administrative	Agriculture	Alternative energy	Energy conservation	Waste management	Transportation
US-CA	0.96	0.72	1.46	0.89	0.84	0.95
GE-US	0.53	1.64	1.50	1.04	0.81	0.89
UK-US	1.12	1.01	1.27	0.67	0.98	0.47
IN-US	1.42	0.60	1.05	0.88	0.58	0.56
US-CN	0.54	0.92	1.60	1.46	0.69	0.89
FR-US	0.61	1.35	1.55	0.94	0.99	0.45
US-JP	0.53	0.95	1.79	1.20	0.64	0.92
GE-FR	0.20	3.50	1.10	0.90	0.69	1.10
CL-GE	0.25	2.02	1.53	1.04	0.81	1.49
KR-US	0.52	0.45	1.75	1.49	0.78	1.08
TW-CN	0.65	0.11	1.49	1.99	0.29	1.26
AT-GE	0.25	0.91	1.25	1.35	0.99	3.10
GE- UK	0.31	3.04	1.31	0.83	0.75	0.79
GE-NL	0.23	0.80	1.60	1.27	1.45	0.77
NL-US	0.46	0.66	2.18	0.85	1.17	0.36
US-IL	1.52	0.57	1.03	0.96	0.36	0.55
US-TW	0.35	0.46	1.60	2.12	0.37	1.72
US-CL	0.80	1.84	1.29	0.95	0.43	0.84
AU-US	1.15	0.83	1.46	0.66	0.76	0.59
JP-KR	0.16	0.17	1.62	2.27	0.85	0.75

Source: Authors' own calculations based on PATSTAT data.

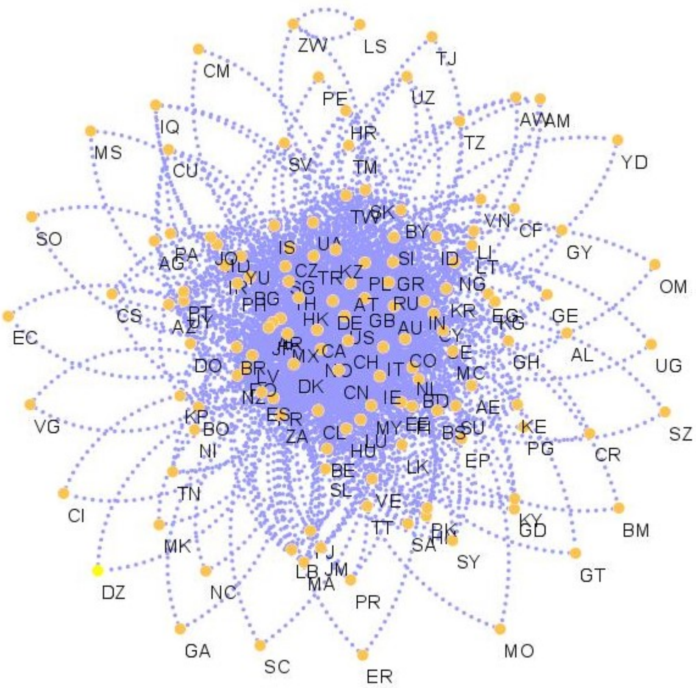
In the final stage of our descriptive analysis, we present the global technological collaboration network in visual form for the years 1995 and 2019.[15] Figure 2.14 shows that, compared with 2019, collaborative innovations in 1995 reveal that the world was less strongly connected. At the centre of Figure 2.14a are the US, Japan, the United Kingdom, Germany, China, Canada, and a number of other developed European economies. Those economies located at the centre of the figure can be considered the leaders in technological collaborative innovation in 1995. Figure 2.14b shows the network for 2019 and reveals that many more economies participate in collaboration and that the world is more closely connected. There is also a notable increase is the number of less developed economies participating in global technological cooperation. However, although the linkages between economies have increased, the leaders remain those economies that were leaders in 1995.

Figure 2.15 shows an equivalent visual representation for the network of collaborative eco-innovation and displays how it has evolved over time. Again, the number of economies and collaborative innovations increased substantially between 1995 and 2019 and again, collaborative eco-innovations are still led by developed economies such as the US, the United Kingdom, Germany, Canada, Japan, and the Republic of Korea. However, by 2019, India and China had moved towards the centre of the network, demonstrating their growing importance as partners in the development of green technologies.

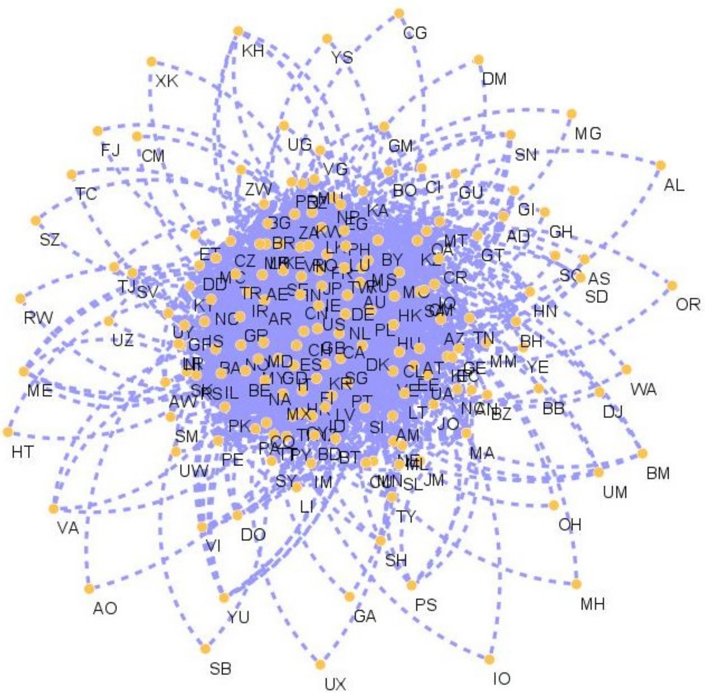
[15] Since 2020 was impacted by COVID in ways we do not yet fully understand, we look at 1995 and 2019.

Figure 2.14: The global collaboration network.

(a) 1995



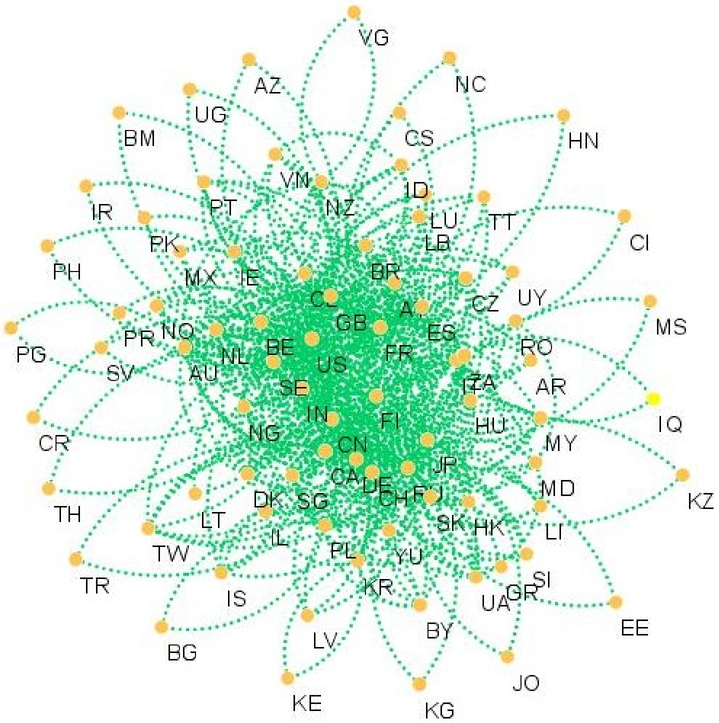
(b) 2019



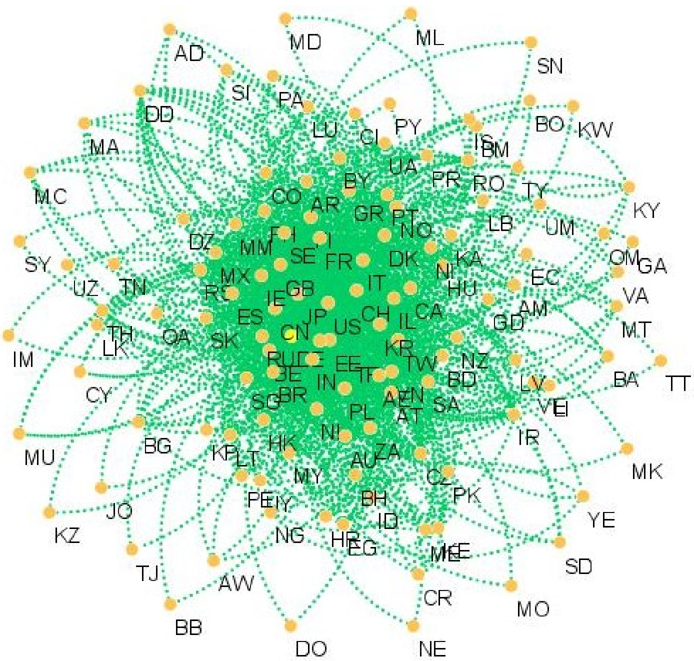
Source: Authors' own calculations based on PATSTAT data.

Figure 2.15: The global eco-collaboration network.

(a) 1995



(b) 2019



Source: Authors' own calculations based on PATSTAT data.

2.5 Innovation and the manufacturing industry

In this section, we describe the development of inventions and collaborative innovations considering just the manufacturing sector. The main finding is that there are significant differences in inventions and collaborative innovations across sectors. Our industry-level analysis is based on a concordance table linking the IPC codes and NACE codes.[16] Using the correspondence table linking NACE codes with IPC codes enables us to map inventions to different sectors in the manufacturing industry.[17]

2.5.1 Trends in manufacturing innovation

The first step is to look at how patent families are distributed across different industries. Figures 2.16 and 2.17 show that the computer and electrical equipment sector has the most inventions and eco-innovations by a considerable margin. The smallest number of inventions and eco-innovations is in the wood and textiles sector. The chemical and non-metallic mineral products sector ranks second in terms of the total eco-innovations over our time period.[18] In summary, the computer, electronic, and electrical equipment sector, machinery and equipment sector, and chemical sector are the top three sectors whether we look at total inventions or eco-innovations. Individual production processes require a substantial level of energy consumption. Given that manufacturing is traditionally one of the highest-polluting sectors, it is reassuring to see how much research activity has taken place in this area of the economy.

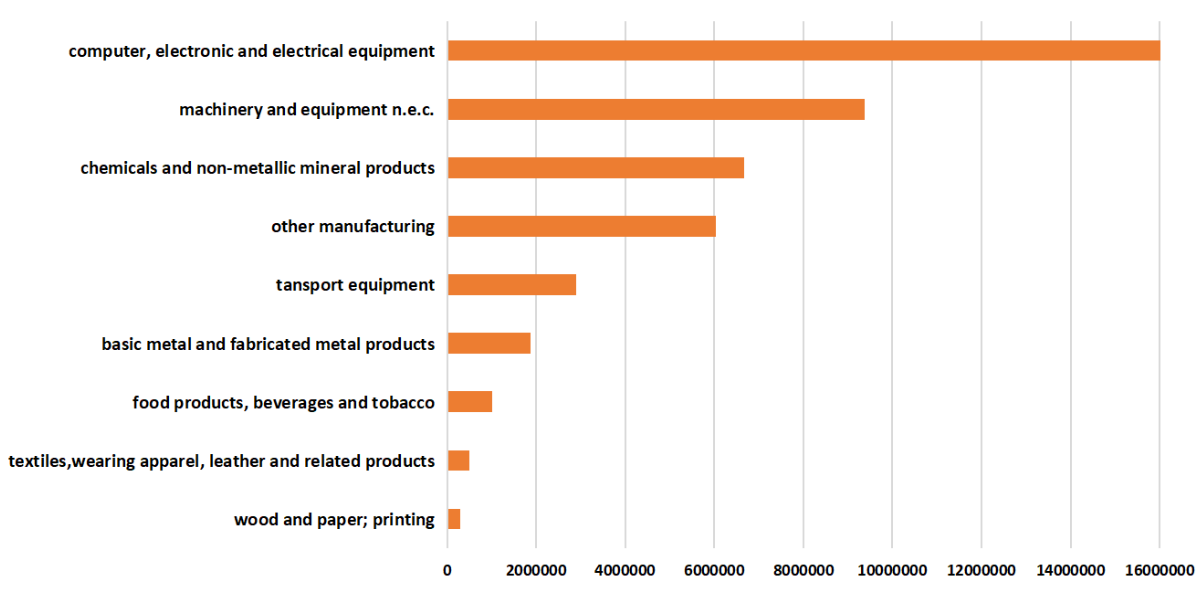
[16]NACE is the standard European nomenclature.

[17]IPC codes are only linked to the manufacturing industry.

[18]Non-metallic mineral products include the production of cement, ceramics, glass, and lime. The conversion of natural minerals through energy-intensive processes characterises the manufacturing industry related to non-metallic minerals.

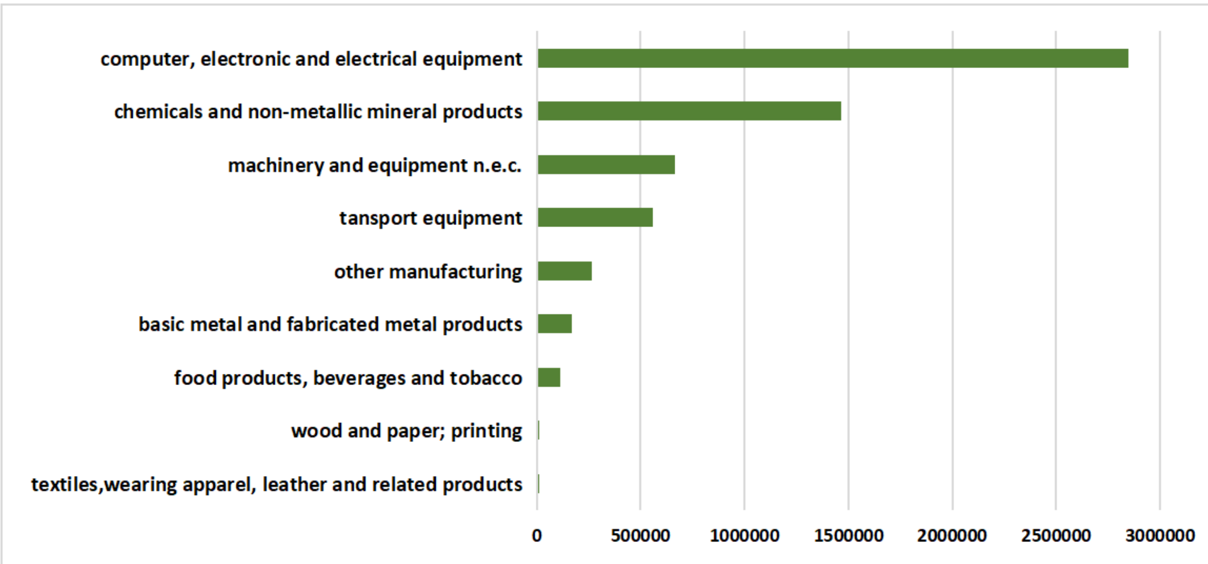
Figure 2.18 presents the number and growth of total inventions and eco-innovations in each industry. Each industry shows a significant increase, with inventions related to electrical products having the fastest growth, followed by the machinery and chemical industries. Figure 2.18b shows that eco-innovations are growing across all industries, although the increase is most rapid for computer technologies. It is worth noting that the chemical and machinery industries also experienced rapid growth. The relatively slow pace of eco-innovation in wood and paper and basic metals is reassuring and reflects the maturity and relatively simple structure of these industries.

Figure 2.16: Inventions in selected manufacturing industries.



Source: Authors' own calculations based on PATSTAT data.

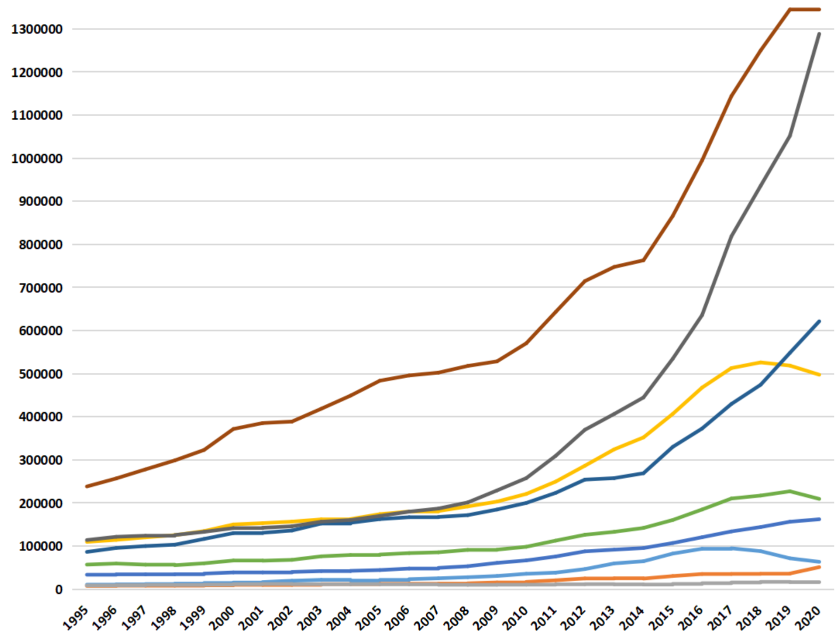
Figure 2.17: Eco-innovations in selected manufacturing industries.



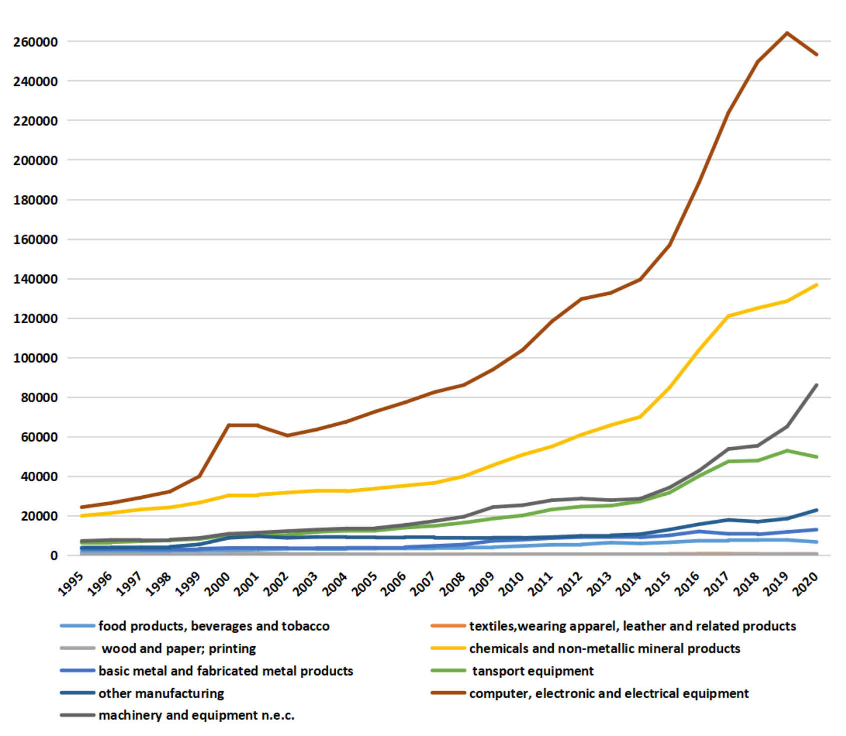
Source: Authors' own calculations based on PATSTAT data.

Figure 2.18: Number of inventions in selected manufacturing industries.

(a) Inventions in selected manufacturing industries.



(b) Eco-innovations in selected manufacturing industries.

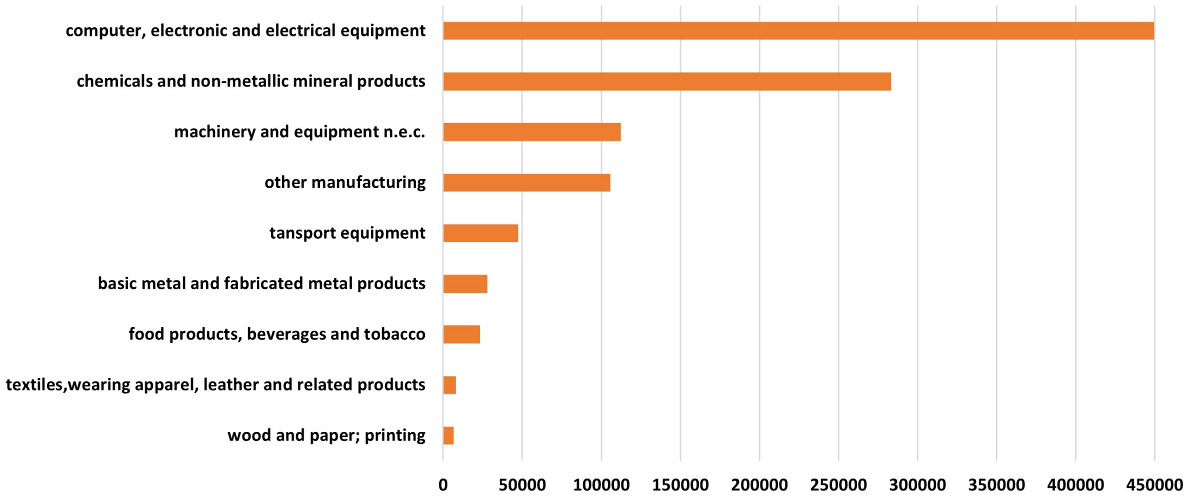


Source: Authors' own calculations based on PATSTAT data.

2.5.2 Trends in manufacturing collaborative innovation

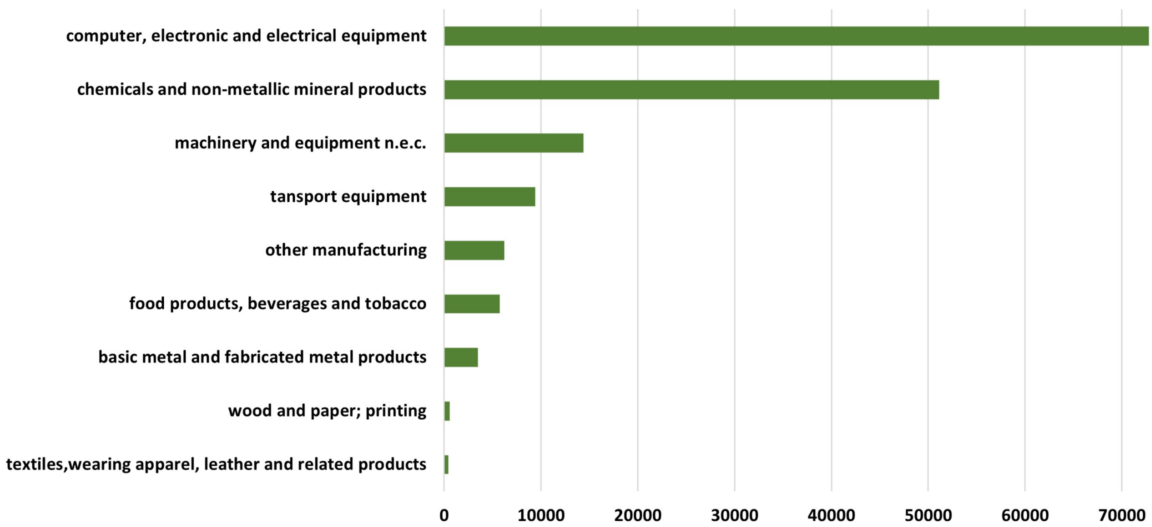
Figures 2.19 and 2.20 present equivalent evidence for collaborative innovations and collaborative eco-innovations for selected manufacturing industries. Compared with other industries, the number of collaborative innovations in the computer and electronics industry and the chemical and non-metallic mineral products industry are significantly higher that those in the other industries. The machinery and equipment industry and the transport industry also have a significant number of collaborative eco-innovations, as might be expected due to the development of the electric vehicle industry.

Figure 2.19: Collaborative innovations in selected manufacturing industries.



Source: Authors' own calculations based on PATSTAT data.

Figure 2.20: Collaborative eco-innovations in selected manufacturing industries.

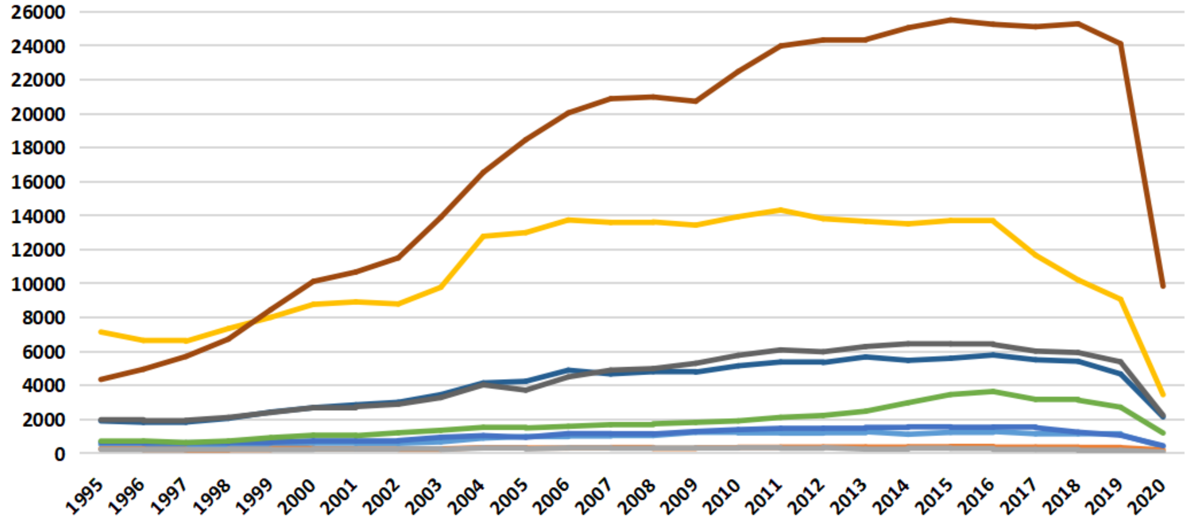


Source: Authors' own calculations based on PATSTAT data.

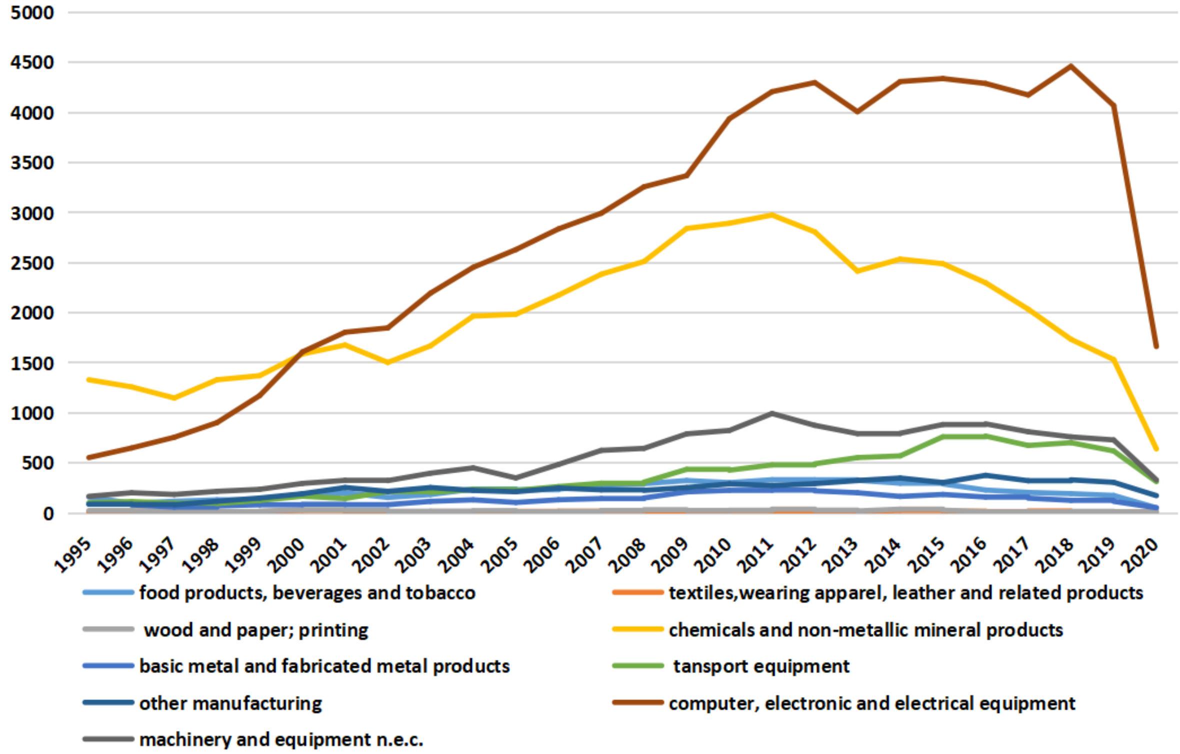
Finally, Figure 2.21 shows how the number of collaborative innovations has changed over time. The fastest-growing sector is the computer, electronic, and electrical equipment industry, which also has the largest increase in the number of collaborative eco-innovations. As we have previously shown, there was a significant drop in the total number of collaborative innovations in each manufacturing sector as a result of the COVID pandemic.

Figure 2.21: The number of collaborative innovations in selected manufacturing industries.

(a) Collaborative innovations in selected manufacturing industries.



(b) Collaborative eco-innovations in selected manufacturing industries.



Source: Authors' own calculations based on PATSTAT data.

2.6 Conclusions and policy recommendations

To better understand global technological innovation, this paper examines the global trends in innovation, collaborative innovation, eco-innovation, and collaborative eco-innovation. The analysis is based on data collected from the PATSTAT database, which provides detailed information on patent families between 1995 and 2020 for each technology field. The purpose of this paper is to understand how innovation and collaborative innovation have changed over time and how these concepts may help mitigate the impact of climate change and allow economies to meet their Paris Agreement obligations. Understanding the role of collaborative innovation is also linked to the debate on how best to foster more resilient GVCs; collaboration and deeper links between economies are likely to play an important role.

This paper presents broad trends but also breaks innovation down by technology fields for both general innovation and eco-innovation. Overall, we find that there was a very significant increase in innovation between 1995 and 2020 as more and more economies developed the internal capabilities that allowed them to undertake the level of R&D that eventually leads to a patent. Although innovation remains strong in the US, Germany, and Japan, it is notable that developing economies have considerably strengthened their innovative capabilities. This trend is reflected in the changing patterns of collaborative innovation, as shown in our visual representation of innovation networks. China and India saw very considerable increases in innovation and to a lesser extent eco-innovation.

The growth in eco-innovation offers hope that human ingenuity will be able to offset some of the most damaging effects of climate change. However, eco-innovation can only really be beneficial if those technologies are quickly and efficiently diffused across the world's economies. When it comes to collaborative eco-innovation, the story is similar but there is some cause for concern. Although the general trend is upward there has been a noticeable decline in the number of collaborative eco-innovations in certain technology fields. This is important for two reasons. First, eco-innovation is often thought of as highly complex, requiring inputs from more than one economy given the enormity of some of the technical problems that need to be overcome. Second, collaboration is more likely to lead to a greater diffusion of these green technologies and hence makes them more likely to have larger global environmental benefits.

To encourage eco-innovation governments may need to pay more attention to subsidies, environmental regulations and policies, R&D investment, and developing their economies' research capacity more generally (Duan, Nie, and Coakes, 2010). There is also the possibility of learning-by-doing effects, whereby economies learn from collaboration and go on to develop larger domestic research capabilities, leading to a broader level of technological upgrading. It is important therefore to look carefully at the reasons for the fall in collaborative eco-innovation in recent years and determine whether this is a result of economies developing stronger domestic capabilities or whether it is part of a broader pattern of de-globalisation, protection of IP, geopolitical tensions more generally (e.g., the US-People's Republic of China trade war), and the perception that firms and governments are facing an increasingly uncertain outlook after the dual shocks of COVID-19.

Greater collaboration between economies at both the intensive and extensive margins should also build in greater resilience. If a economy develops collaborative research with a larger number of economies, this portfolio approach to research should leave the economy in a stronger position if any one partner is subject to an external shock (economic or political). However, this assumes a larger number of short supply chains. When supply chains become longer, this inevitably creates weak points. This is why GVC resilience is best created by having complex networks in which any one point of failure can be quickly filled by another equally competent supplier or research team.

Although policymakers have different solutions to stimulate eco-innovation, it is less clear whether these same methods also encourage collaborative eco-innovation. Governments should consider which green technology field they have an innovation advantage in and which economies are their most important collaborative innovation partners. In the case of developing Asia and the Pacific, it is important to identify core strengths and weaknesses so certain sectors or individual firms can be encouraged to seek international partnerships and in some cases helped financially and helped to identify possible partners, regardless of where they are located geographically. To build more resilience into the research system, governments may wish to encourage collaboration across a range of developed and developing economies at different stages of the research process.

Developing Asia and the Pacific may also consider gathering information on the eco-innovation performance of member economies based on a series of indicators (similar in nature to the European Commission, which publishes an EU eco-innovation index based on 18 different indicators). The Asian Development Bank (ADB) already sets clear climate targets and has project-level disclosure for all of its climate-related projects. Other policies that may have direct and indirect impacts on future eco-innovation and collaborative eco-innovation include its energy transition mechanism (ETM) in Indonesia and the Philippines and the ASEAN Green Recovery Platform, which matches ADB funding with pledges from the EU, the United Kingdom, and others to de-risk private investment in green infrastructure. Similarly, the ADB Ventures climate technology funds aim to promote venture-stage innovation in the hope that this triggers innovation and future global cooperation. The ADB Southeast Asia innovation hub was also set up to provide innovative financing solutions to help attract greater levels of green and sustainable investment in Southeast Asia. The ADB's Faces of Innovation report in 2020 provides a good summary of the innovation powers in Asia and the Pacific and the role of sustainability (**ADBfaces**).

One of the most pressing issues, following a rapid increase in global energy prices, is to promote and help fund innovation in green energy-related projects. For example, the ADB invested $8.5 billion in clean energy and energy efficiency projects between 2016 and 2020, with a considerable investment going into wind and solar power. The broader 2009 Energy Policy of the ADB has also spent over $42 billion on energy-related projects, although this includes fossil fuel-related projects. The ADB Strategy 2030 has a focus on low-carbon technologies; this should support existing cooperative agreements.

Policymakers can also help firms overcome some of the legal and IP concerns that other economies may have by having a strong rule of law and IP protection, including through the patent system. Policymakers can also help if mediation is required when there are disagreements on time frames, ownership, pricing, and how to deal with litigation if initiatives break down. If these challenges can be overcome, there are plenty of growth opportunities for companies, especially in the area of eco-innovation and clean tech development. The need for cooperation is also exacerbated by rapidly changing technologies such that it is difficult for any one economy to have complete expertise (in, for example, AI, large language models such as ChatGPT, and cloud computing). The rapidly changing technological frontier also has implications for supply chain resilience and again supports the argument for working with a range of different partners to shorten supply chains and get exposure to different advanced technologies.

Finally, the world is facing a period of great uncertainty and risk. This backdrop may act as a brake on future collaborative research between firms based in different economies. To pull back from collaborative innovation, especially in environmental-related research, could lead to greater risks. Fostering more resilient supply chains goes hand in hand with building stronger collaborative research links, and the two can be considered to be complementary. Policies that strengthen GVCs are likely to have a similar impact on patterns of collaborative innovation. Given the close links between trade and innovation, supply chain disruptions due to the COVID-19 will have had a cooling effect on collaborative innovation. There is some hope that recent policies from the US, such as the CHIPS Act, the EU's Green Deal Industrial Plan, and China's recent 'Green Development in a New Era' plan for the industrial sector will mean considerable investment in eco-innovation. It is yet to be seen whether this will result in more or less collaborative eco-innovation and how these policies will impact overall trade patterns and the structure of existing supply chains.

This paper presents overall trends in innovation and collaborative innovation, with an emphasis on the environment. However, there is more research to be done to address the limitations related to data quality and the use of patent data to capture innovation. Research looking at the determinants of innovation and eco-innovation and an examination of policy effectiveness in encouraging innovation would be particularly welcome. If we are to understand how we can green global value chains and improve GVC resilience, it is important to understand the impact of collaborative innovation on the carbon content of trade. These remain topics for future research.

Chapter 3

Collaborative Eco-innovation along Global Value Chains: Evidence from OECD countries

3.1 Introduction

In the last two decades, international trade flows have been profoundly changed by the rapid growth of global value chains (GVCs), leading the world into what has been called the 'Age of Global Value Chains' (Antràs, 2020a; Byahut et al., 2021; Antràs and Chor, 2021). Falling trade barriers and improvements in transportation and production technologies over the last twenty years has increasingly lead to the design, production and assembly of goods and services being located across multiple and geographically dispersed countries. One of the implications of the fragmentation of production is that products and services can cross borders (often the same borders) a number of times in the form of exports, imports, or transfers of value-added (Baldwin and Venables, 2013; Raei, Ignatenko, and Mircheva, 2019). However, the globalisation of production processes and the resulting increase in international trade has important environment implications (Christoff and Eckersley, 2013; D. I. Stern, 2017). According to Copeland, J. S. Shapiro, and M. Scott Taylor, 2021, traded goods accounts for more than a quarter of worldwide emissions leading to calls for firms, usually downstream, to clean up or 'green' their global value chains.

One of the most heavily promoted solutions to greening GVCs is through the direct and indirect impact of eco-innovation (EI), defined as innovation that could prevent pollution, save energy and protect the environment during production (Sinclair-Desgagné, 2013). However, the eco-innovation process is complex and requires a broad range of skills, knowledge and technological inputs (Barbieri, Marzucchi, and Rizzo, 2020). The complexity of the EI process is one reason why international collaboration is so often talked about as one of the main channels by which technological progress in the area of environmental technologies can take place. One of the main benefits associated with collaborative innovation in the area of the environment is the possibility that subsequent innovations are able to diffuse more quickly around the world. However, to date there is little research on understanding the extent to which collaborative eco-innovation takes place and how cooperation of this type is influenced by GVC networks.

The purpose of this paper is to understand the relationship between GVCs and international collaborative innovation in the area of green technologies. Access to external sources of knowledge and the breadth and depth of knowledge collaboration have been shown to be important to the success of any EI process (De Marchi, 2012; Horbach, Rammer, and Rennings, 2012). The development of new green technologies is likely to be enhanced if there is cooperation between suppliers, traders, exporting countries and importing countries. As such, enhancing collaboration along GVCs may help countries green their GVCs and help them achieve certain Sustainable Development Goals as part of the 2030 Agenda for Sustainable Development and meet their Paris Agreement on Climate Change obligations. While there is relatively well-established literature that has examined the relationship between EI and GVCs more generally, (Costantini et al., 2017; Y. Sun, Bi, and Yin, 2020; Qu, Shao, and Z. Cheng, 2020), there are few studies that examine the relationship between collaborative eco-innovation across countries and GVCs and the role eco-innovation plays in greening GVCs.

Hence, there is growing pressure from customers and legislators for companies to take responsibility for reducing their environmental footprint of their products. The push for countries to green their GVCs is clearly illustrated by the European Union (EU) who issued a series of environmental regulations that require EU members to reduce hazardous substance emissions during mining, production, transportation, and consumption.[1] One reason for the legislation is that within GVCs, the dirtiest part of the production process more often than not take place upstream and is more likely to be located in developing and emerging economies. The result is a gap between where pollution is produced and where it is consumed (Copeland, J. S. Shapiro, and M. Scott Taylor, 2021). At the extreme. trade-induced pollution can ultimately impact the stability and resilience of GVCs (Antràs, 2020b). Hence, it is important to understand the degree to which pollution is embodied in trade and how to promote supply chain sustainability (Lyubich, J. Shapiro, and Walker, 2018).

Turning to the existing literature, cooperation with suppliers that are part of the same value chain has proven to improve efficiency, reduce market risk, and can complement the technological

[1]The laws include the ‘Packaging and Packaging Waste Directive’ (1994) and other environmental regulations aimed at restricting pollution.

strategy of the firm looking to upgrade their technology stock (Klassen and Vereecke, 2012; Sako and Zylberberg, 2019). A similar line of thinking can be applied to eco-innovation in that cooperation with suppliers may stimulate environmental technology upgrading (Melander, 2018). For example, in a study of the automotive industry, Geffen and Rothenberg (2000) found that a strong partnership with suppliers located upstream in the value chain was a strong driving force of green technology innovation. Similarly, Vachon (2007) showed that cooperation in the packaging and printing industry between suppliers and their downstream customers had a positive impact on eco-innovation.

With innovation more generally, technical cooperation across countries has been shown to facilitate technology transfer (Duan, Nie, and Coakes, 2010; D. B. Audretsch, Lehmann, and Wright, 2014). Hence, there is every reason to expect that global green technological collaboration would also promote information sharing and green technology transfer (R. Lema and A. Lema, 2012) with several studies highlighting the importance of GVCs as a channel for disseminating knowledge which in turn can stimulate eco-innovation (Ph Aghion, Hemous, and Veugelers, 2009; S. K. S. Wong, 2013; J. J. Ferreira, Fernandes, and F. A. Ferreira, 2020). Similarly, Arfi, Hikkerova, and Sahut (2018) show that eco-innovation in multinational firms (MNEs) is strongly impacted by the availability of internal and external knowledge. Glachant et al. (2013) also argues that knowledge, skills and technology can move between countries through international trade in intermediate goods (often as part of a GVC). At the sector level, a study by F. Zhang and Gallagher (2016) on the Photovoltaic (PV) industry of China shows that eco-innovation in developing green technologies can occur due to both national and international innovation processes but is stimulated by knowledge exchange through GVCs. However, Bi, P. Huang, and Xiangxiang Wang (2016) shows that compared to technologically intensive industries (such as the PV industry), there is no significant relationship between participating in GVCs and eco-innovation for traditional manufacturing industries. Hence, if we find that trade impacts eco-innovation we are most likely to find an effect in new green technology sectors.

This paper also contributes to the literature on international technological collaboration (Rodríguez, Nieto, and Luis Santamaría, 2018; Y. Li et al., 2021). Existing studies have examined patterns of internationalisation in research (Miguélez, 2018; S. P. Kerr and W. R. Kerr, 2018) and trends in international patenting (Breschi and Lissoni, 2009; H. Chen et al., 2017; Miyamoto and Takeuchi, 2019). This literature shows that geographical factors such as the distance between two countries has an negative impact on collaborative innovation, while cultural proximity, such as sharing a common language or strong diaspora networks, stimulates collaborative innovation (Lundquist and Trippl, 2013; Miguélez, 2018; S. P. Kerr and W. R. Kerr, 2018; Luis Santamaría, Nieto, and Rodríguez, 2021). In terms of eco-innovation, Haščič, Johnstone, and Kahrobaie (2012) used patent data to show that OECD countries that were members of the 'International Technology Agreement' have 90% more collaborative inventions compared with non-members for seven crucial climate change mitigation technologies.

The approach we take in this paper is to examine the GVCs that exist between 36 OECD countries and China (their main trading partner), for the period 2005 to 2018 to examine how different aspects of GVCs impact eco-innovation and collaborative eco-innovation measured using patent data from The European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT). The reason for including China is that while in 2005 China accounted for 22% of total OECD imports, by 2018 this share had risen to 34%. In addition, as Picci (2010) highlights, there has been a significant increase in the offshoring of R&D activities to countries, such as China, which has intensified the internationalisation of new knowledge.[2] To capture the degree of international collaborative innovation we use patent data as a measure of innovation and eco-innovation both domestically (using local inventors only) and collaboratively invented between members of our sample countries. More specifically, we apply a structural gravity model to assess the relationship between bilateral GVC links and collaborative innovation (Haščič, Johnstone, and Kahrobaie, 2012). GVC links are captured in numerous ways including trade in intermediates, trade in final products, total bilateral exports, domestic value-added (DVA) content of gross exports, the DVA embodied in international final demand and the origin value-added (OVA) embodied in international exports.

To summarise our contribution, first we examine the relationship between trade along GVCs and collaborative innovation with a focus on eco-innovation using a wide range of GVC engagement measures. Second, we are the first to use patent data to represent countries' research ability in the context of collaborative eco-innovation between countries. Third, while previous studies have tended to use the OECD definition of EI which classifies green technologies into three different types: environmental-related technologies, climate change adaption technologies, and the sustainable ocean economy, in this paper we use the richer United Nations Environmental Programme Classification, which categorises green technologies into seven technologies fields according to the production activities and product use rather than the impact on the environment.[3]

To briefly summarise our results, we find that exports in intermediate products, total bilateral

[2]OECD members include Australia (AU), Austria (AT), Belgium (BE), Canada (CA), Chile (CL), Czech Republic (CZ), Denmark (DK), Estonia (ES), Finland (FI), France (FR), Germany (DE), Greece (GR), Hungary (HU), Iceland (IS), Ireland (IE), Israel (IL), Italy (IT), Japan (JP), Korea (KR), Latvia (LV), Lithuania (LT), Luxembourg (LU), Mexico (MX), Netherlands (NL), New Zealand (NZ), Norway (NO), Poland (PL), Portugal (PT), Slovak Republic (SK), Slovenia (SI), Spain (SP), Sweden (SE), Switzerland (CH), Turkey (TR), United Kingdom (UK), United States (US).

[3]For example, the technologies related hybrid vehicles are categorised as 'transportation' in our research but is part of 'climate change mitigation technologies' in the OECD classification.

exports, the DVA content of gross exports and DVA embodied in foreign ultimate demand has a positive impact on collaborative eco-innovation. These findings imply that the value added embodied in trade flows leads to greater bilateral collaborative eco-innovation. Specifically, a 1% increase in the DVA content of total exports and DVA embodied in foreign demand will increase collaborative eco-innovation roughly by 2.2 and 2.9 units on average, respectively.

The remainder of the paper is organised as follows. Section two explains the flows of valued-added embodied in trade through GVCs. Sections three and four explain the definition of international technological collaboration and the links to international technological collaboration along GVCs. Sections five and Six describe the data and present some stylised facts. Sections seven and eight describe our empirical methodology and the main results, respectively. The final section concludes.

3.2 International Collaboration Innovation

Central to our research question is the definition of collaborative innovation (also called collaborative innovation). According to the literature, collaborative innovation is the process of making a new innovative breakthrough after cooperation between investors or firms based in different countries (S. M. Lee, Olson, and Trimi, 2012). Collaborative innovation is commonly thought to refer to the joint effort of multiple parties with different characteristics and resources that come together to develop new, or upgrade existing, technologies (Saragih and J. D. Tan, 2018). Collaborative innovation can occur between any two countries, companies, universities or individuals. De Prato and Nepelski (2014) explain how collaborative innovation is often the outcome of the segmentation of the invention process on a global scale, a process in which inventors from different countries interact and are able to combine information and knowledge from various sources (Sachwald, 2008). The international division of innovation across countries means that the innovation process is first subdivided and finalised by inventors located in different countries which in turn strengthens the flow of knowledge between countries (Archibugi and Iammarino, 2002; De Prato and Nepelski, 2014).

As innovation includes new inventions and upgrades to existing technologies (S. M. Lee, Olson, and Trimi, 2012), there have been a number of different proposals on how to measure innovation, reflecting the different stages of the innovation cycle (Haščič and Migotto, 2015a).[4] From an 'input' perspective, widely used indicators include research and development (R&D) expenditure, R&D personnel and innovation expenditure (including the intangible investments such as design expenditures) (Rene Kemp, 2008; Enkel, Gassmann, and Chesbrough, 2009; Hall and Josh Lerner, 2010; Schot and Steinmueller, 2018; Duque-Grisales et al., 2020). However, R&D related measures only reflect the investment in resources devoted to the innovation process but do not capture the outcome of this expenditure (Haščič and Migotto, 2015b). Moreover, and for the purpose of this paper, R&D related measures do not allow a systemic distinction between R&D expenditure related to the environment and more general R&D expenditure. Hence, to capture the 'outcome' of the R&D expenditure, process innovation, product improvement, and the patent counts have been used (Bottazzi and Peri, 2003; Kahn, 2018).

In this paper, we define an innovation as a technological breakthrough that have been granted patent protection. Compared with other measures, patent data has clear advantage as a direct measurement of the outputs of the invention process (Bottazzi and Peri, 2003; Lanjouw and Schankerman, 2004; Nagaoka, Motohashi, and Goto, 2010). Moreover, patent data is widely available and can be thought of as a rigorous measure of innovation since all inventions that

[4] Stages of the innovation cycle include technology development, technology diffusion, and technology adoption.

apply for protection need to undergo a thorough assessment process. However, there are some limitations to the use of patent data. For example, not all inventions are patented meaning that a patent count is not necessarily a comprehensive measure of innovation (Haščič and Migotto, 2015a; Durán-Romero and Urraca-Ruiz, 2015).[5]

An important advantage of patent data is that it allows us to identify international collaboration in the innovation process. Hence. we follow the existing literature and define international collaborative innovation as inventions that have been patented and are derived from the cooperation between inventors who reside in different countries (Haščič, Johnstone, and Kahrobaie, 2012).[6] We rely on the extensive information provided in patent documents to identify inventors, patent offices, patent classification and inventors' country of residence. Unfortunately, despite the richness of patent data, it is not possible to identify inventions whose inventors are located in different countries but have the same nationality. Equally, we are not able to identify inventions which have two inventors who reside in different countries but who work for the same firm. However, since the focus of this paper is on GVCs, and given the significant role that multinationals (MNEs) play in GVCs, we believe that collaborative innovation within the international structure of MNEs are an important channel through which countries connected by GVC links may collaborate in research.

To measure the degree of collaborative innovation of green technologies we classify inventions

[5]Many 'inventions' such as copyrights, are included in intellectual property rights (IPR) regimes but cannot be patented in a patent office. These 'inventions' are not included in our research because we are concerned with the technologies that have practical use in production and even have a positive effect on the environment, especially innovation that come in the form of international cooperation.

[6]In this paper, we focus on the bilateral patterns of collaborative innovation. For example, if an invention has three inventors, one residing in China, one residing in Germany, and one residing in Japan, it would be classified as a collaborative innovation between China and Germany, China and Japan and Japan and Germany. Similarly, if an invention has two inventors residing in China and two in Japan, it would be counted only once as a collaborative innovation between China and Japan.

according to their impact on the environment using United Nation Environmental Programme (UNEP)'s list of environmentally sound technologies (ESTs) that have the ability to improve environmental performance compared with other types of technologies (Costantini et al., 2017). ESTs are those green technologies that could protect the natural environment, reduce pollution, use resources in an effective way, recycle more and handle residual wastes in a more environmentally way than the technologies for which they are substitutes (Pasquali, 2018).

To identify an eco-innovation we rely on the list of green international patent classification (IPC) codes developed by the IPC Committee of Experts who identify patented innovation that are relevant to the ESTs as specified in the United Nations Framework Convention on Climate Change (UNFCCC).[7] ESTs are also classified into different green technological fields according to their use and each of these green technical fields is associated with a series of unique green IPC codes (René Kemp and Pearson, 2007; Costantini et al., 2017). Table 3.1 describes the specific green technology fields in the IPC Green Lists. We classify an innovation as an eco-innovation if at least one of the IPC codes associated with the patent is on the green IPC list.

[7]Our paper focuses on a complete list of IPC green codes generated by the World Intellectual Property Organisation (WIPO): https://www.wipo.int/classifications/ipc/en/ (accessed in October, 2022).

Table 3.1: ESTs fields classified according to IPC Green Lists

ESTs fields	**Specific technology**
Alternative energy production	Bio fuels, fuel cells, hydro energy, etc.
Transportation	Vehicles in general, marine vessel propulsion, etc.
Energy conservation	Low energy lighting , storage of electrical energy, etc.
Waste management	Waste disposal, pollution control, etc.
Agriculture /forestry	Forestry techniques, soil improvement, pesticide alternative, etc.
Administrative, regulatory or design aspects	Static structure design, pollution credits, etc.
Nuclear power generation	Nuclear engineering

Source: Own selection in terms of Green IPC Lists.

3.3 Slicing up Global Value Chains

Antràs (2020a) defines a GVC as a sequence of processes associated with the production of goods and services that will be purchased by consumers. Along this sequence of processes, value is continuously added to the production process and it may be imported by many countries, reprocessed and then re-exported. The value-added imported from other countries is referred to as foreign value added, while domestic value-added reflects the value generated within a specific country and added to the overall production process (Koopman, Z. Wang, and Wei, 2014). The concept of GVCs, therefore, describes the phenomena of using foreign value-added (FVA) and of transferring domestic value-added (DVA) when products are then to be exported (Antràs, 2020a).

In this paper, we study the consequences of the transnational flow of value-added and decompose trade flows into various components to represent the flow of value-added within GVCs based on macro measurements (Antràs and Chor, 2021).[8] Data sources like the World Input-Output Table

[8]Macro measurements focus on the value-added from transactions at the aggregate country level or country-industry level which are different to so-called micro measurements which consider the cross-border trade between buyers and suppliers at the firm-level (Antràs and Chor, 2021).

(WIOT) dataset allow us to track the trade in value added along GVCs between pairs of countries (Hummels, Ishii, and Yi, 2001; Koopman, Z. Wang, and Wei, 2014; Borin and Mancini, 2019). The OECD TiVA database, which is based on the WIOT, combines input-output linkages data at the country and industry level with trade statistics in order to track cross-country and cross-industry value added and to develop indicators of global production fragmentation (Borin and Mancini, 2019). According to the OECD TiVA database, the flow of products and services along value chains has four component parts: the origin of value-added, importers, exporters, and final consumers. Production activities along a global value chain can be thought of as simple or complex and is illustrated in Figure 3.1 (Z. Wang et al., 2017). Simple GVC activities capture the direct trade of value-added that only crosses one international border once. Within simple GVCs, the exporting country is where the value-added is generated and the importing country is that of final demand. Complex GVC activities correspond to processes where the value-added crosses international borders several times before reaching final consumers. In complex GVC activities, importing countries could be exporters or final consumers.[9]

[9]For complex GVCs, if the importer country is the final destination, the importer country will be the final demand country. However, if the importer country is one of the many nodes in the whole value chain, imports will be re-exported to other countries. In this case, this country acts as the importer. Furthermore, there are situations where the importer country will consume part of the imports, and re-process and export the other part. Under these circumstances, for the consumed imports, the country is the destination of final demand, and for the exported part, the country acts as an importer.

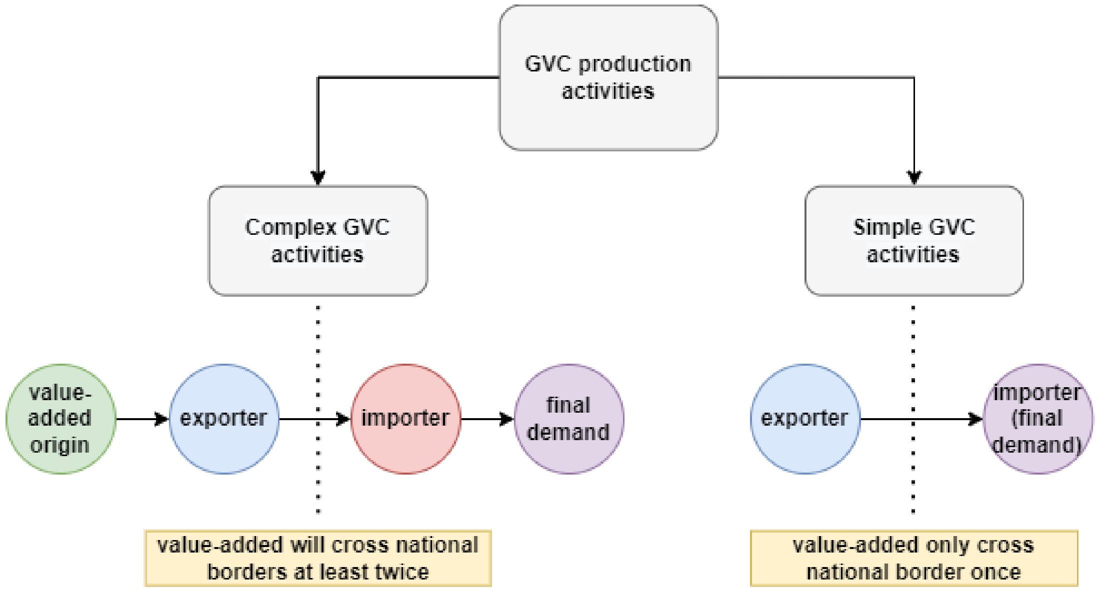


Figure 3.1: Decomposition of GVC activities

Source: Own calculations based on the instructions of OECD TiVA database

In this paper, we adopt six measures of GVC links, each representing a distinct bilateral flow of value-added: (1) 'exports of intermediate products', (2) 'exports of final products', (3) 'total gross exports', (4) 'DVA content of gross exports', (5) 'DVA embodied in foreign final demand' and (6) 'origin value added (OVA) content of gross exports' (Guilhoto, Webb, and Yamano, 2022). Intermediate products exported from country i to country j[10] constitute direct exports of intermediate products that will be further processed and consumed in country j, in which case country j is both the importer and final consumer country, or re-exported by country j, in which case country j is just an importer.[11] For the export of final products, country i is the final step in the value chain before the final goods reach their final demand destination in country j[12]. Total bilateral gross exports from country i to country i correspond to the sum of the exports of intermediate products and the exports of final products.

[10]The exported intermediate products may contain both FVA from other countries and DVA from country i.

[11]Direct exports represent trade flows where exporters sell products to importers directly without going through another country. Figure B.1 in Appendix illustrates the gross exports of intermediate products between two countries.

[12]Figure B.2 in Appendix describes the direct exports of final products between country i and country j.

The DVA generated in country i is transferred to country j through direct exports of intermediates and of final products (DVA content of gross exports). An intermediate or final product exported by country i may contain FVA imported from other countries. To measure the DVA content of intermediates and final products, we only focus on the the value-added generated by country i that will be exported to country j. When the DVA from country i is transferred to country j through the exporting of intermediate goods, country j can be the final consumer or importer. If country j is the final consumer, the DVA from country i will be further processed and consumed in country j. Country j will act as an importer when the DVA generated by country i is further processed and re-exported to a third country. The DVA generated by country i may also be transferred to country j through the exporting of final products, in which case country j is the final demand country. Unlike the first two measures of GVC links, exports of intermediates products and exports of final goods, which measure the gross value of direct exports between country i and country j, the DVA content of gross exports only captures the value-added originating from country i and embedded in the exports of intermediate inputs and of final goods to country j.

DVA could also be transferred to other countries through exports destined for final demand. The indicator 'DVA embodied in foreign final demand' captures the connection between upstream domestic industries and downstream foreign customers. The DVA generated in country i and embodied in the foreign final demand of country j could be transferred through the direct exports of final products form country i to country j or through the indirect exporting of intermediate products. In the case of indirect exports, the DVA generated in country i will be exported, to a third country, for further processing before reaching consumers in country j. This latter measure of GVC links captures flows of value added that are exchanged between two countries without a direct trading link.

Finally, the 'OVA content of gross exports' illustrates how the value of a country's gross exports is an accumulation of value added generated in other countries.[13] The value added generated in country i is transferred to country j, through direct export, to be further processed and exported by country j as intermediate products and final goods. Therefore, the value-added from country i will be transferred to the world by being embedded in the exports of country j.[14]

3.4 Data and Stylised Facts

We focus on 36 member countries that have joined the OECD before 2019 and on China for the time period between 2005 and 2018.[15] OECD members not only include countries like the US, UK, Germany, and Japan, which possess strong research capabilities, but also countries such as Poland, Türkiye, and Mexico, which do not rank highly in developing eco-innovation, as discussed in Chapter 2. This selection allows us to explore technological cooperation not only between countries with robust R&D capacities but also between those with limited R&D capabilities. Moreover, the OECD works closely with non-members large economies, such as China which is now one of the largest trading partners and one of the most important innovation partners of OECD members.

Patent data is collected by the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT). PATSTAT is a comprehensive database containing over 100 million patent documents collected from more than 90 patent offices all over world (De Rassenfosse,

[13]It also includes the DVA generated in country i that is re-exported by country j to country i.
[14]Details could be found at Figure B.5 in Appendix.
[15]For the full country list see Table D.5 in Appendix.

Kozak, and Seliger, 2019). This dataset includes patent documents about inventors' addresses, application dates, unique identification number of each patent family and other patent classification information. Patent documents also include the legal event data of more than 40 patent offices included in the EPO Global Legal Event Data (INPADOC). We focus on simple patent families as a measure of innovation to avoid double-counting problems.[16] Information about the residence of inventors allows us to identify collaboratively invented innovation. We are therefore able to measure the total number of collaborative innovation (total, eco and non-eco) at a bilateral level for 37 countries over a 14 years period.

GVCs related data is extracted from the OECD's 2021 edition of the TiVA database which provide data on bilateral trade in value-added up to 2018. We measure the trade variables in a bilateral, non directional, way that reflects the measurement of bilateral collaborative innovation. For example, the total DVA embodied in gross exports between country i and country j is the sum of the DVA exported by country i to country j and the DVA exported by country j to country i.

Table 3.2 presents the summary statistics for the main variables of interest. As we can see, there are considerably more inventions and eco-inventions that are not collaborative in a given year. In terms of the trade variables, there is a greater value of intermediates than final goods on average. Not surprisingly, the DVA variables are of a similar size and larger than the OVA measure. The mean for the GVC position is negative, which suggests that on average there is more backward than forward participation (which is explained later). The dependent variables (collaborative innovation, collaborative eco-innovation, and Collaborative non-eco innovation)

[16] A patent family is a collection of patent documents that all cover the same invention that has been protected in several patent offices. The technical content protected by the law is considered the same, and the technical content used for the application is identical. The difference between patents within a patent family pertains to the patent office where the invention is protected.

are based on the Patstat data ranging from 2006 to 2020, while the independent variables (trade-related variables) and other control variables are extracted from the TIVA data from 2005 to 2018.

Table 3.2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Total collaborative innovation	9990	57.575	240.136	0	4022
Collaborative eco-innovation	9990	8.475	36.041	0	553
Collaborative non eco-innovation	9990	49.099	205.398	0	3680
Total innovation	9990	15903.861	35875.579	38	256803
Eco-innovation	9990	2565.942	5812.472	1	29721
Bilateral exports (USD million)	9324	14537.965	45804.336	2.6	721853.13
Intermediate exports (USD million)	9324	8365.585	26076.718	1.2	441597.81
Final products export (USD million)	9324	6172.379	20348.631	1.4	373749.22
DVA exports (USD million)	9324	11199.269	36707.041	2.2	616035.19
DVA embodied in foreign final demand (USD million)	9324	10736.236	35118.529	5.9	681700.5
OVA embodied in foreign exports (USD million)	9324	3072.592	7626.171	1.223	105993.36
GDP per capita (US dollars)	9324	37123.888	16365.637	5041.555	116334.73
GVC position	9324	-0.294	0.544	-1.705	1.139
Common language (dummy)	9990	0.066	0.248	0	1
Distance (km)	9990	5371.312	5240.326	59.617	19586.18

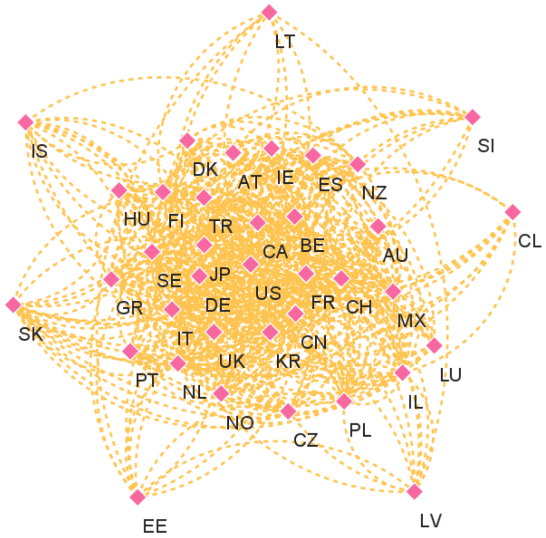
3.4.1 Mapping the International Networks of Co-Innovation

In order to analyse the patterns of international collaborative innovation, we follow the literature (De Prato and Nepelski, 2014; Y. Li et al., 2021) and draw on the idea of neural network analysis to represent collaborative innovation as ‘neurons’ that connect pairs of countries. A neural network allows us to visualise the technological cooperation between countries and to capture the changes in cooperation patterns over time. Figures 3.2 and 3.3 present the network of collaborative innovation between the countries in our sample for total collaborative innovation and for collaborative eco-innovation. Nodes represent countries while links capture countries' bilateral relationships. Countries at the centre of the network have a greater number of links with other countries and therefore play a leading role in international collaborative innovation.

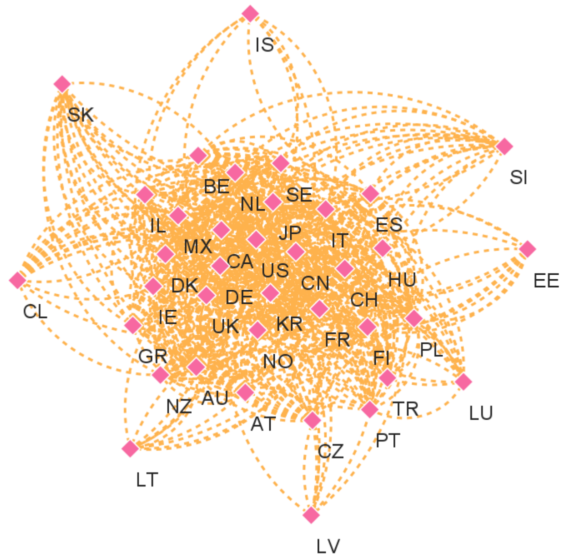
According to Figure 3.2, the centre of the network consists of high income countries such as the US, the UK, Germany and other developed European countries. However, in comparison to the start of our period of analysis, by 2018 the collaborative innovation network becomes larger, as illustrated by the increased number of links. Another significant change over the time period is the role played by China. By 2018, China has moved to the centre of the network becoming one of the leading countries in international technological collaborations. A larger number of countries appear to becoming more tightly connected with the centre of the network, possibly because countries prefer to collaboratively innovate with partners that already have a significant level of technological cooperation with others (De Prato and Nepelski, 2014). Figure 3.3 represents the network of international technological collaboration in eco-innovation and shows that the number of collaborative eco-innovation has increased over time. The network on collaborative eco-innovation is also centred around developed countries such as the US, the UK, Germany, Canada and Japan. Compared with 2005, Figure 3.3b shows that countries are cooperating more closely, which is shown by an increase in the number of links. Finally, Figure B.8, in the Appendix, shows the rank of country-pairs in total collaborative innovation, collaborative eco-innovation and collaborative non-eco innovation for the countries in our sample in terms of average annual number of collaborative innovation. The US and China collaboratively invent the largest number of patents, eco and non-eco, with an average of 3,868 patents per year. Almost all top country-pairs include the US as a partner highlighting the dominant role played by the US in international technological collaborations.

Figure 3.2: Technological collaboration links among OECD members and China

(a) 2005



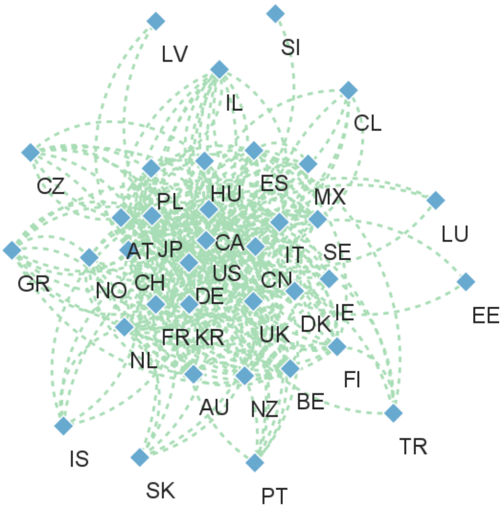
(b) 2018



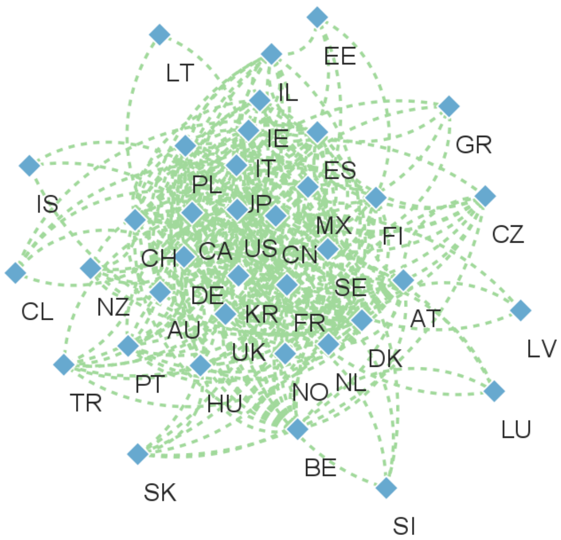
Source: Own calculation based on PATSTAT database.

Figure 3.3: Eco technological collaboration links among OECD members and China

(a) 2005



(b) 2018



Source: Own calculation based on PATSTAT database.

3.4.2 Stylised fact on Trade

Figure 3.4 compares the value of bilateral exports of the countries in our sample between 2005 and 2018. The size of the circle represents trade volumes. The larger the circle, the greater the value of the country's exports to the OECD.[17] The US, China and Germany are the three largest exporters to OECD countries across our time period. However, in comparison with 2005, China replaces the US as the largest exporter. The colour-coded lines capture the value of bilateral trade between the top three countries and their five largest trading partners.[18] Thicker lines indicate a greater value of bilateral trade between two countries. In 2018, China replaced Canada and became the largest trade partner of the US. We find very similar patterns when considering the DVA content of exports. Figure 3.5 shows that China replaced the US to become the largest trade partner of the OECD in terms of the DVA content of exports. Moreover, compared with 2005, nearly all OECD countries increased their exports in DVA to other OECD countries.

Figure 3.6 describes the patterns of exported DVA embodied in foreign final demand and shows that China moved from the third position in 2005 to become the largest exporter of DVA embodied in foreign final demand in 2018, while Germany moved from second-largest to the third-largest exporter. Moreover, the DVA embodied in foreign final demand between Germany and China increased considerably between 2005 and 2018. Although France and the UK are not in the top three, they are some of the largest exporters of DVA in final demand compared to other European countries.

Figure 3.7 shows the OVA embodied in foreign exports traded between the countries in our

[17]Country i's exports to the OECD is the total exports from country i to all OECD members.

[18]The volume of bilateral exports between two countries is measured by the sum of gross exports between the trade partners. For example, the volume of bilateral exports between China and the US is the sum of gross exports from China to the US and gross exports from the US to China.

sample. The US, Japan and Germany are the largest sources of OVA embodied in final exports. Although China exported the most intermediate products, final products and DVA to the OECD, the proportion of value-added from China re-exported by the OECD is small. We can infer that most OVA exported by China will be processed and consumed by importing countries in the OECD, which may imply that compared with countries such as Germany, Japan and the US, China adds value at the downstream stages of the value chain.

Figure 3.8 provides a visual representation of various countries' positions in GVCs, based on the average of their position indices from 2005 to 2018. The GVC Position Index is measured by the upstreamness of a country within a value chain. Following C. Sun et al. (2019), we calculate a country's GVC position as follows:

$$*GVCPi = \ln(1 + forward\_participation\_i) - \ln(1 + backward\_participation\_i) \quad (3.1)$$

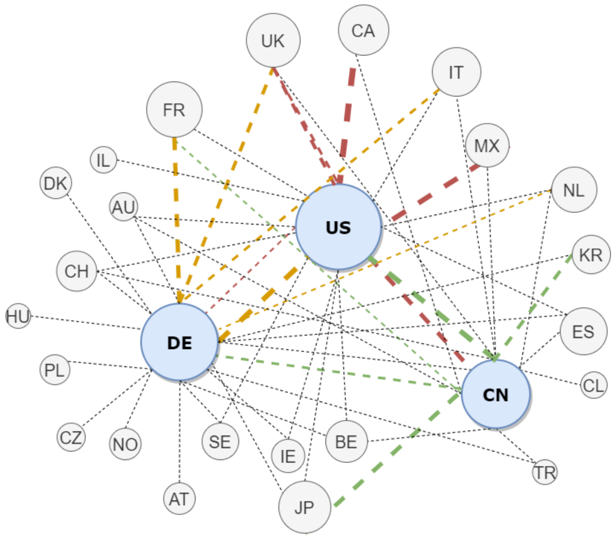
where forward participation is measured as the share of domestic value added embodied in world's exports of total gross exports by the source country. Backward participation is measured as the share of foreign value added embodied in exports of total gross exports of the world.[19] The greater a country's GVCP value, the closer it is to the upstream of the global value chain. Upstream countries typically engage more in the provision of intermediate materials and creative design, while downstream countries focus more on product processing and sales. In the case of developed countries like the US, Germany, Japan, Norway, and the UK, their positions near the upstream end of the GVC can be attributed to their highly developed and diverse economies. These countries are home to numerous multinational corporations that are often

[19] $Forward\_participation = \frac{DVA\_exportij}{total\_exporti}$ $backward\_participation = \frac{FVA\_export_{ij}}{total\_exporti}$, where i is exporting country and j is the importing country which is the world.

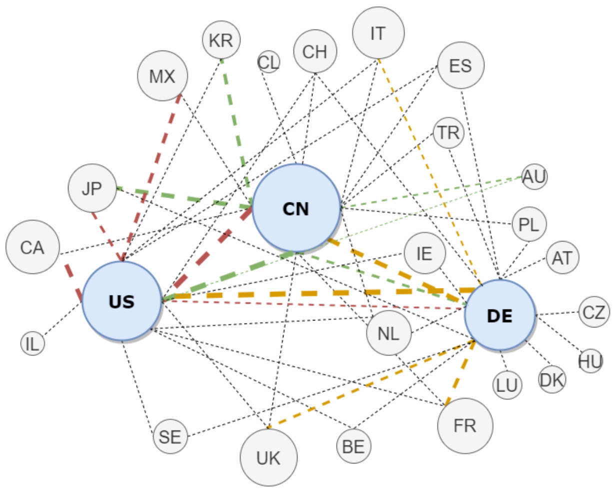
involved in high value-added activities such as R&D, design, and the production of complex goods. These activities tend to be at the upstream end of the GVC. Furthermore, these countries have highly skilled workforces and advanced infrastructure, which support their involvement in the upstream activities. They also have sophisticated legal and regulatory environments that protect intellectual property, which is crucial for innovation and design activities. China's position is above the average value but not at the very upstream end of the GVC can be attributed to its rapid economic development and increasing technological capabilities. Over the past few decades, China has made significant strides in moving up the value chain. It has invested heavily in infrastructure, education, and technology, transitioning from a low-cost manufacturing hub to a global leader in various high-tech industries. However, compared to the very developed economies, China may still be in the process of transitioning towards more upstream activities, as sectors may still be more focused on manufacturing and assembly operations, which are typically more downstream activities. Thus, its position in the GVC reflects this mix of upstream and downstream activities.

Figure 3.4: Bilateral exports among OECD members and their largest trade partners

(a) 2005



(b) 2018

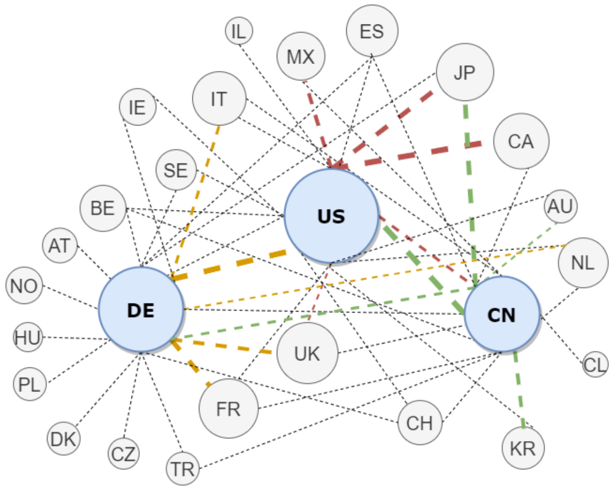


Source: Own calculation based on OECD TiVA database.

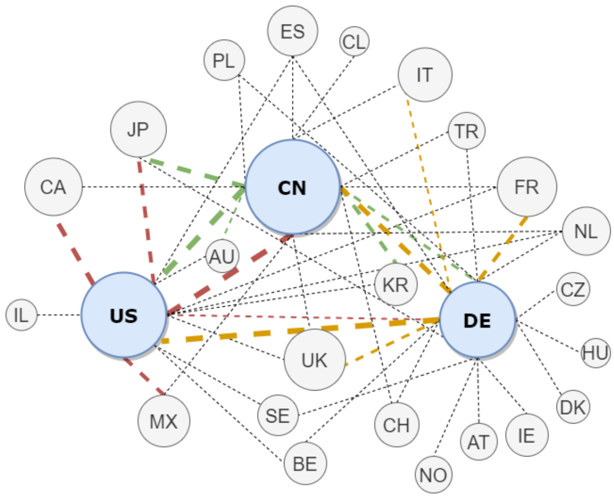
Note: Red lines, yellow lines and green lines capture the five largest trade partners (from the OECD) of the first three countries (three largest circles) in total exports.

Figure 3.5: DVA content of exports transferred among OECD members and their largest trade partners

(a) 2005



(b) 2018

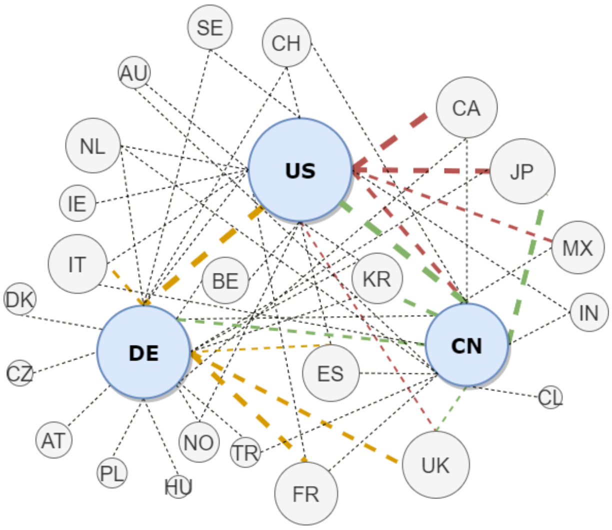


Source: Own calculation based on OECD TiVA database.

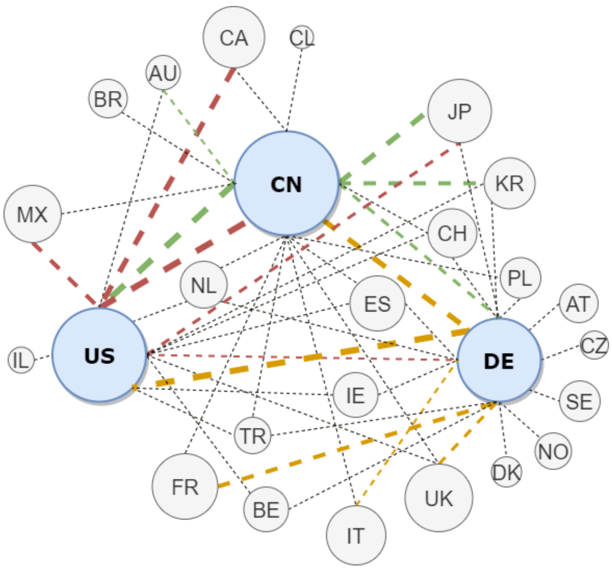
Note: Red lines, yellow lines and green lines capture the five biggest trade partners (from the OECD) of the first three countries (three largest circles) in exporting DVA.

Figure 3.6: DVA embodied in foreign final demand transferred among OECD members and their largest trade partners

(a) 2005



(b) 2018

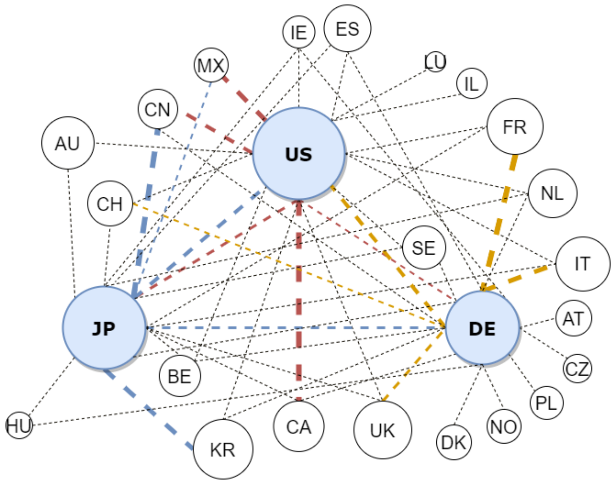


Source: Own calculation based on OECD TiVA database.

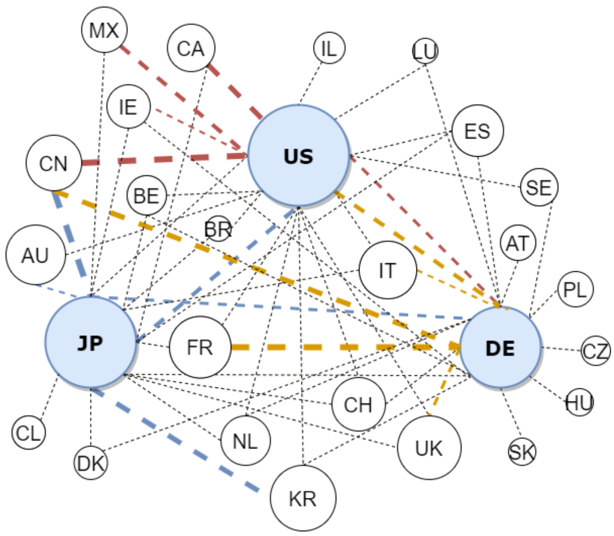
Note: Red line, yellow line and green line capture the five largest trade partners (from the OECD) of the first three countries (three largest circles) in exporting DVA used to produce final demand of importing countries.

Figure 3.7: Origin value-added embodied in exports transferred among OECD members and their largest trade partners

(a) 2005



(b) 2018



Source: Own calculation based on OECD TiVA database.

Note: Red lines, yellow lines and blue lines capture the five largest trade partners (from the OECD) of the first three countries (three largest circles) in exporting OVA which will be re-exported by importing countries.

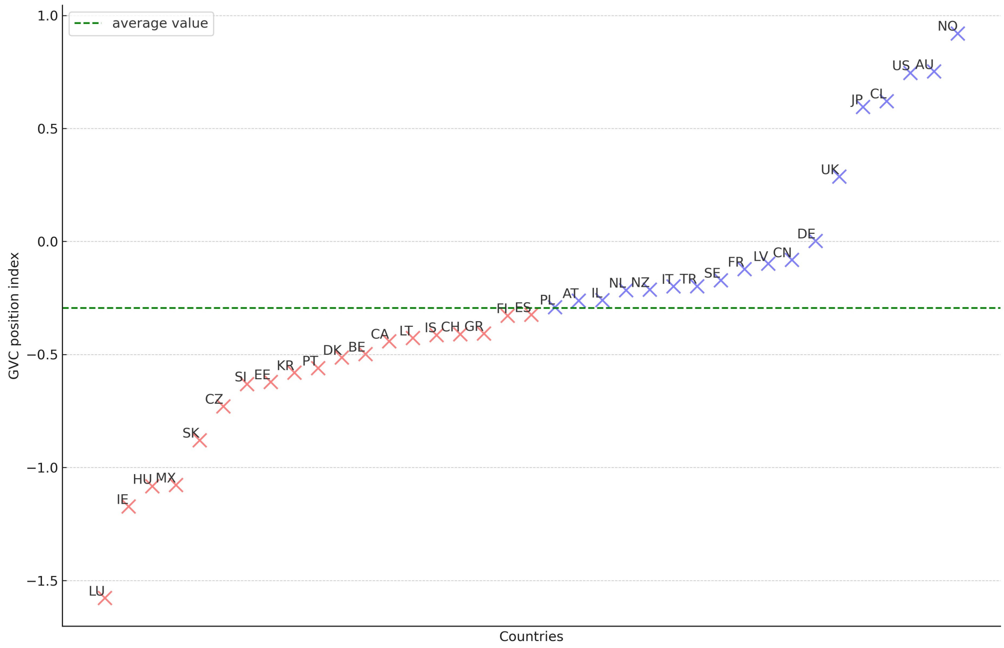


Figure 3.8: Average value of GVC position index for OECD + China

Source: Own work based on the instructions of OECD TiVA database

3.5 Methodology

3.5.1 Gravity Model

We model bilateral collaborative innovation with the following structural gravity equation based on the works of Anderson and Van Wincoop (2003) and Silva and Tenreyro (2006):

$$Y_{ijt} = S_i M_j d_{ij}^e n_{ij} \tag{3.2}$$

where Y_{ij} measures total collaborative innovation, collaborative eco-innovation or non-eco collaborative innvoation by country i and country j. S_i and M_j are country level characteristics, d_{ij} is a vector of bilateral level variables and n_{ijt} is the error term.

A log-linear transformation of equation (1) is not appropriate given that our dependent variable is a count variable (count of collaborative innovation) and that it includes a large number of zeros.[20] We therefore follow the literature (Weidner and Thomas Zylkin, 2021) and estimate Equation (1) with a Poisson Pseudo Maximum Likelihood (PPML) estimator with three-way fixed effects. There are many advantages to using PPML method to estimate a gravity model. In the presence of overdispersion, the model will not satisfy the conditions of the Poisson model traditionally used in the context of count data. However, PPML implements a Poisson regression with standard errors that are robust in the presence of overdispersion (Correia, Guimarães, and Tom Zylkin, 2020). Moreover, it is possible to embed multi-dimensional fixed effects within a PPML estimator (Correia, Guimarães, and Tom Zylkin, 2020).

PPML with three-way fixed effects has been shown to be able to address endogeneity concerns associated with unobservable variables and to provide consistent estimates even with small T (Weidner and Thomas Zylkin, 2021). The three-way fixed effects include country-time varying fixed effects and country-pair fixed effects. The country-time varying fixed effects control for time varying differences between countries, such as the level of economic development, R&D capabilities or the stringency of environmental regulations (Bai, 2009). Country-pair fixed effects capture time non-varying variables that represent the unique bilateral characteristics between a pair of countries, such as distance, common borders and common language. Moreover, the innovation process is lengthy and characterised by uncertainty and risk. We expect current GVC relationships to foster technological collaborations between countries, however these collaboration will need time to come to fruition. To account for the time needed for innovation

[20] In our sample, around 23% of the observations have zero collaborative innovation, and about 50% of the observations have zero collaborative eco-innovation.

process, we lag the explanatory variables by one year in our main specification and by 2 years in a robustness check.[21]

In light of the above, to model the relationship between cooperation along GVCs and international technological collaboration, we estimate the following equations, where ij refers to country-pairs and t refers to time, :

$$COINV_{ijt} = exp(Intermediate_{ijt-1}, \alpha_{it}, \alpha_{jt}, \alpha_{ij}) + \epsilon_{ijt} \tag{3.3}$$

$$COINV_{ijt} = exp(Final_{ijt-1}, \alpha_{it}, \alpha_{jt}, \alpha_{ij}) + \epsilon_{ijt} \tag{3.4}$$

$$COINV_{ijt} = exp(Bilateral_{ijt-1}, \alpha_{it}, \alpha_{jt}, \alpha_{ij}) + \epsilon_{ijt} \tag{3.5}$$

$$COINV_{ijt} = exp(DVAEXP_{ijt-1}, \alpha_{it}, \alpha_{jt}, \alpha_{ij}) + \epsilon_{ijt} \tag{3.6}$$

$$COINV_{ijt} = exp(DVAFFD_{ijt-1}, \alpha_{it}, \alpha_{jt}, \alpha_{ij}) + \epsilon_{ijt} \tag{3.7}$$

$$COINV_{ijt} = exp(OVAEXP_{ijt-1}, \alpha_{it}, \alpha_{jt}, \alpha_{ij}) + \epsilon_{ijt} \tag{3.8}$$

$COINV_{ijt}$ captures the number of patented inventions (total, eco or non-eco) (claimed or unclaimed priorities) whose innovators are residents in countries i and j.[22] Year t is defined by the priority date of the invention (i.e. the first day on which a worldwide patent application was filed).

The key explanatory variables are a set of variables describing the transfer of value added between countries along GVCs. The bilateral exports of intermediates ($Intermediate$) is the

[21] In the regression with one-year (two-year) lagged independent variables, the dependent variables (collaborative innovation, collaborative eco-innovation, and collaborative non-eco innovation) are based on the Patstat data ranging from 2006 to 2019 (2007 to 2020), while the independent variables (trade-related variables) are extracted from the TIVA data from 2005 to 2018.

[22] Priority claims are a useful and critical method of linking later-filed patents with earlier-filed patent applications. As a priority application, an earlier filed application usually must have common elements to claim priorities.

sum of the gross exports of intermediate goods and services between trade partners. The bilateral exports of final products ($Final$) is the sum of the gross exports of final goods and services between trade partners. The total bilateral exports ($Bilateralexport$) is the sum of the gross exports which include exports in intermediates and final products between trade partners. Domestic value added content of gross exports ($DVAEXP$) measures the sum of total value added generated in the domestic economy, specifically country i and country j, which is exported between the two countries. Domestic value added content of foreign final demand ($DVAFFD$) represents the sum of total value-added produced in the origin country, i or j, embodied in the final demand of country j or i. The origin value added content of foreign exports (OVA) measures the domestic valued added produced in origin country, i or j, and embodied in the exports of foreign country (j or i).

3.6 Results

3.6.1 Base line Results

Tables 3.3 and 3.4 present the baseline results for the countries in our sample, while Tables 3.5 and 3.6 presents results where the independent variables are lagged by 2 years. The geographical dispersion among the countries in our sample is substantial, suggesting that their DVA might necessitate extensive transnational transit, potentially traversing multiple national borders, before arriving at the country of final demand. These countries not only serve as significant exporters of DVA to one another, they are also pivotal collaborators in the domain of eco-innovation. The results support the principal hypothesis that cooperation in GVCs stimulates international technological collaboration and leads to higher collaborative innovation. Although collaboration based on the trade of final goods necessitates an extended duration to stimulate eco-innovation

(Table 3.5), all the other GVC variables positively stimulate collaborative eco-innovation with one year lag. For instance, a one per cent increase in DVA exports (log_dvaexp) will result in 2.140 additional eco collaborative innovation two years after which represent a 25% increase at the mean. A one percent increase in the OVA embodied in foreign exports (log_ova) results in 2.875 more eco collaborative innovation (or a 30% increase) on average after two years, making it the most effective trade route for fostering this type of innovation. GVC links have a positive impact on non-eco innovation as well, however the magnitude of the effect is not as large as in the case of eco-innovation. For example, a one percent increase DVA exports leads to a 17% increase in the patented collaborative non-eco innovation. In the case of Collaborative non-eco innovation, the DVA embedded in final demand has the strongest impact and results in a 23% increase in the number of patents.

We also estimated the model focusing on OECD members. Results are presented in Table B.2 and Table B.3 in Appendix. The results also support the principal hypothesis that cooperation in GVC stimulates collaborative eco-innovation. Specifically, the coefficients of exports of intermediate products (log_intermediate), total bilateral exports (log_Bilateralexport), DVA content of gross exports, DVA embodied in foreign final demand and OVA content of gross exports (log_ova) are all statistically significant and positive in stimulating total collaborative innovation, collaborative eco-innovation and collaborative non-eco innovation after one year. In the case of the exports of final products, the impact on collaborative eco-innovation is positive and significant after two years.

The geographical factor and cultural differences impact collaborative innovation and the diffusion of technology through trade, especially for eco-innovation (Montobbio and Sterzi, 2013). The results show that with or without the largest partner of OECD member countries, trade still has significant positive impacts on collaborative eco-innovation. Our results also demonstrate that cooperation with developing countries is beneficial to eco-innovation whether or not they have a direct trade relationship.

Table 3.3: Average marginal effects of exports related variables for OECD members + China (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	8.974***			2.401***			7.177***		
	(2.084)			(0.742)			(1.889)		
log_Final		5.799***			1.147			4.946**	
		(2.157)			(0.753)			(1.993)	
log_Bilateralexport			9.720***			2.269***			8.044***
			(2.353)			(0.838)			(2.144)
Observations	8,778	8,778	8,778	7,459	7,459	7,459	8,722	8,722	8,722
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table 3.4: Average marginal effects of value-added related variables for OECD members + China (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	10.235***			2.232***			8.576***		
	(2.376)			(0.837)			(2.157)		
log_dvaffd		12.028***			2.608**			10.127***	
		(3.198)			(1.117)			(2.894)	
log_ova			8.852***			3.032***			6.626***
			(2.208)			(0.793)			(2.011)
Observations	8,778	8,778	8,778	7,459	7,459	7,459	8,722	8,722	8,722
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table 3.5: Average marginal effects of exports related variables for OECD members + China (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Eco Collaborative innovation			Collaborative non-eco innovation		
log_Intermediate	8.218***			1.717**			6.878***		
	(2.018)			(0.747)			(1.830)		
log_Final		7.244***			1.917**			5.837***	
		(2.205)			(0.778)			(2.022)	
log_Bilateralexport			9.866***			2.196***			8.218***
			(2.300)			(0.845)			(2.093)
Observations	8,792	8,792	8,792	7,449	7,449	7,449	8,750	8,750	8,750
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***$p<0.01, $**$p<0.05, $*$p<0.1

Table 3.6: Average marginal effects of value-added related variables for OECD members + China (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	10.443***			2.140**			8.829***		
	(2.304)			(0.838)			(2.094)		
log_dvaffd		13.495***			2.583**			11.718***	
		(3.130)			(1.132)			(2.831)	
log_ova			8.517***			2.875***			6.336***
			(2.158)			(0.797)			(1.962)
Observations	8,792	8,792	8,792	7,449	7,449	7,449	8,750	8,750	8,750
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

3.6.2 Robustness Checks

As a robustness check, we construct instrumental variables (IV) for the trade-related variables and employ the IV Poisson Generalised Method of Moments (GMM) regression approach, which serves to alleviate potential endogeneity issues. In the model, a three-way fixed effect is initially employed to address the endogeneity problem caused by omitted variables, such as environmental regulations, trade policies, etc., which are absorbed by the fixed effect. However, there potentially remains an issue of reverse causality in the model. We expect GVC links to impact knowledge exchanges between the two countries, thereby influencing collaborative innovation. For instance, significant changes in trade volumes could alter the level of engagement in joint R&D, exchange of key technical personnel and lead to collaborative innovation. However, it is possible that that the number of collaborative innovation may affect bilateral trade in return. For instance, collaboration in innovation could lead to the introduction of new products or services which may translate in new GVC links and an increased volume of GVC trade. A careful examination of this phenomenon would likely require robust instruments to isolate exogenous variations in bilateral trade.

To address endogeneity issues, we follow the literature and estimate an IV Poisson estimator with a Bartik (1991) instrument.[23] The Bartik (1991) instrument, also known as the "shift-share" instrument, is frequently employed to address endogeneity issues. The IV Poisson estimator, also known as the Exponential Conditional Mean model, is often used to estimates the parameters of a Poisson regression model where some regressors are endogenous. The Generalised Method of Moments (GMM) estimator implemented in IV Poisson regressions is discussed in Windmeijer and Santos Silva (1997) and Wooldridge (2010). To construct the instruments for trade variables,

[23]Wong (2022) is an example of using a "shift-share" instrument in the context of a gravity model of trade.

we follow the approach of Bartik (1991):

$$Z_{ijt} = X_{iAjt} * \frac{X_{ij2000}}{X_{iA2000}} \tag{3.9}$$

$$X_{iAjt} = X_{iAt} - X_{ijt} \tag{3.10}$$

Where the first term X_{iAt} is country i's exports to all its trading partner in set A.[24] X_{ijt} is the trade transaction between country i and country j at time t. X_{iAjt} is the sum of country i's export to all its trade partners (in set A) except for country j at time t. $\frac{X_{ij2000}}{X_{iA2000}}$ is the lagged exports share of country i to country j, five years prior to the year 2005. The use of a shift share instrument based on lagged export shares which can help alleviate the simultaneity bias resulting from the use of contemporaneous export shares (Wong, 2022).

Indeed, the Bartik (1991) instrument serves as a robust tool in capturing exogenous variations in trade between two specific countries (say, country i and country j). These exogenous variations may arise from changes in global economic conditions, alterations in policy, or other factors not intrinsically linked to the bilateral trade relationship. The instrument's ability to isolate such exogenous changes allows us to estimate more accurately the impact of trade modifications on innovation and to mitigate the risk of the results being confounded by external variables. By considering the total exports from one country to all of its partners, as well as to a specific partner, and incorporating lagged export shares, the instrument could also effectively minimise the simultaneity bias. This methodology proves particularly valuable where the causal relationship between trade and innovation could potentially be obscured by other intervening factors.

[24] Set A could be OECD members and China or OECD members only, which depends on the regression. Country i's exports could be exports in goods, DVA or OVA. It is calculated based on the explanatory variables.

Given the application of the IV Poisson GMM regression method, we are unable to control for fixed effects. Consequently, in the robustness check, we have incorporated additional variables to control for the research ability, economic size, geographical and cultural proximity and GVC position of countries i and j.[25] TP_i and TP_j measure the R&D capacity of country i and country j - and are constructed as an unweighted sum of innovations (total, eco or non-eco) invented by country i and country j, respectively. GDP_i and GDP_j represent the economic size of countries i j (GDP per capita measured in US dollar). A dummy variable $comlangij$ indicates whether two countries share a common official language and controls for cultural proximity and log_DIS_{ij} measures the distance between countries i and j to capture geographical proximity.[26] Finally, $GVCP\_i$ and $GVCP\_j$ measure the GVC position of country i and country j.

Table 3.7 presents the results of the first-stage regression, demonstrating the validity of the instrumental variable (IV).[27] A valid instrument should show a strong and significant coefficient in this first-stage regression, indicating that the instrument is highly correlated with the potentially endogenous explanatory variable and thus well-suited to predict it in regressions. The results indicate that the instrumental variables (IVs) are significantly associated with the endogenous variables. Such an association underscores the validity of these instruments in isolating the causal effect of the explanatory variables on the dependent variable, thereby mitigating potential endogeneity bias in the estimation process. Tables 3.8 and 3.9 present our findings and confirm the results from our main specification. We find a positive and significant effect of GVC related trade on collaborative innovation in general and collaborative eco-innovation in particular. In this analysis, the coefficients of the core variables demonstrate a significant increase compared

[25]"iv-poisson" is not valid with fixed effects due to the incidental parameter problem.

[26]The data related to the common language and the distance between countries is extracted from the CEPII database.

[27]For only OECD members, the first stage resutlts are presented in Appendix.

to the baseline results. Specifically, a 1% increase in dvaexp leads to an average increase of approximately 5.8 units in the number of collaborative eco-innovations, while a 1% increase in ova results in an increase of about 5.6 units. This substantial rise in coefficients is primarily attributed to the limitations of the IV Poisson GMM approach used in this study, which struggles to control for fixed effects. The incorrect application of fixed effects can yield inconsistent results. To enhance the robustness of our estimates, control variables such as technological progress (TP) have been incorporated into the regression.

Our results also show that inventors from two countries that are physically close to each other are more likely to collaborate. (De Prato and Nepelski, 2014; Moaniba, H.-N. Su, and P.-C. Lee, 2020). Countries are also more prone to collaborate when they share similar cultural proximity, e.g. have the same official language (Ardito et al., 2019). Research ability and trade partners' economic size also have a significant and positive influence on collaborative innovation, which proves that strong R&D capabilities and sound economic development are conducive to stimulating technological collaboration (Ma, Y. Lee, and C.-F. P. Chen, 2009; De et al., 2020).

International trade is not only an exchange of goods and services, but also a process of technology and knowledge dissemination. This exchange of technology and knowledge can inspire new innovation. For example, when a company in one country starts importing goods from another, more advanced country, they may learn new technologies and methods related to the production of these goods. This learning can occur through reverse engineering, imitation, or adaptation of technology. Besides, global trade allows companies to establish relationships more easily with supply chain partners in other countries. These close relationships can encourage collaborative innovation between trading partners, improvements in products, increases in production efficiency, or solutions to problems within the supply chain. In more detail, suppliers may innovate to provide higher quality or lower-cost inputs, or they may work with the purchasing company to collaboratively develop new products or streamline production processes.

Table 3.7: First stage results of IV for OECD members + China

	1	2	3	4	5	6
VARIABLES	Intermediate	Final	Bilateralexport	dvaexp	dvaffd	ova
log_INS_Intermediate	0.870***					
	(0.005)					
log_INS_Final		0.860***				
		(0.005)				
log_INS_Bilateralexport			0.872***			
			(0.005)			
log_INS_dvaexp				0.865***		
				(0.005)		
log_INS_dvaffd					0.900***	
					(0.004)	
log_INS_ova						0.878***

	1	2	3	4	5	6
VARIABLES	Intermediate	Final	Bilateralexport	dvaexp	dvaffd	ova
						(0.005)
log_TP_i	0.084***	0.059***	0.070***	0.076***	0.055***	0.064***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
log_TP_j	0.075***	0.064***	0.067***	0.072***	0.043***	0.074***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
DIS_ij	-0.125***	-0.086***	-0.104***	-0.113***	-0.066***	-0.131***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
comlangij	0.072***	0.177***	0.106***	0.115***	0.094***	-0.070***
	(0.021)	(0.019)	(0.019)	(0.019)	(0.014)	(0.018)
GVCPi	-0.104***	0.041***	-0.049***	-0.036***	-0.005	-0.085***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.007)	(0.009)
GVCPj	-0.110***	-0.059***	-0.097***	-0.078***	-0.020***	-0.141***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.007)	(0.009)

	1	2	3	4	5	6
VARIABLES	Intermediate	Final	Bilateralexport	dvaexp	dvaffd	ova
log_GDP_i	-0.178***	-0.173***	-0.172***	-0.164***	-0.162***	-0.166***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.008)	(0.010)
log_GDP_j	-0.014	-0.058***	-0.029***	-0.022**	-0.045***	-0.031***
	(0.012)	(0.011)	(0.011)	(0.010)	(0.008)	(0.010)
Constant	2.734***	3.255***	2.942***	2.795***	2.810***	2.838***
	(0.176)	(0.161)	(0.160)	(0.157)	(0.120)	(0.155)
Observations	9,324	9,324	9,324	9,324	9,324	9,324
R-squared	0.950	0.956	0.957	0.960	0.974	0.957

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: IV Poisson GMM results of exports related variable for OECD members + China (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	29.961***			5.663***			24.855***		
	(2.350)			(0.688)			(2.082)		
log_Final		30.987***			5.794***			25.817***	
		(2.390)			(0.797)			(2.132)	
log_Bilateralexport			30.784***			5.766***			25.577***
			(2.366)			(0.723)			(2.106)
log_TP_i	21.472***	21.074***	20.934***	3.422***	3.350***	3.304***	18.149***	17.901***	17.756***
	(1.352)	(1.241)	(1.304)	(0.482)	(0.407)	(0.444)	(1.208)	(1.119)	(1.169)
log_TP_j	19.678***	19.285***	19.098***	2.992***	2.942***	2.899***	16.913***	16.607***	16.452***
	(1.060)	(0.917)	(0.978)	(0.375)	(0.312)	(0.341)	(0.952)	(0.821)	(0.880)
DIS_ij	-3.895***	-5.377***	-4.295***	-0.407	-0.669*	-0.462	-3.294***	-4.585***	-3.671***
	(1.344)	(1.077)	(1.220)	(0.354)	(0.349)	(0.341)	(1.201)	(0.963)	(1.093)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	46.111***	43.903***	44.657***	7.608***	7.288***	7.354***	38.641***	36.805***	37.455***
	(2.381)	(2.288)	(2.296)	(0.605)	(0.559)	(0.567)	(2.064)	(1.999)	(2.002)
GVCPi	4.084*	-0.269	1.841	1.759**	1.620*	1.613**	2.525	-1.553	0.479
	(2.195)	(2.203)	(2.183)	(0.809)	(0.845)	(0.819)	(1.955)	(1.995)	(1.961)
GVCPj	11.317***	6.711**	9.461***	3.549***	2.707***	3.179***	8.100***	4.353	6.596**
	(3.372)	(3.368)	(3.372)	(0.802)	(0.706)	(0.754)	(2.976)	(2.980)	(2.979)
log_GDP_i	14.786***	13.942***	14.037***	3.220***	2.945***	3.054***	12.425***	11.974***	11.898***
	(2.358)	(2.431)	(2.351)	(0.843)	(0.867)	(0.845)	(2.093)	(2.163)	(2.090)
log_GDP_j	22.786***	27.294***	24.061***	0.132	0.812	0.297	21.357***	25.206***	22.454***
	(3.867)	(3.886)	(3.892)	(0.892)	(0.809)	(0.847)	(3.427)	(3.448)	(3.452)
Observations	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table 3.9: IV Poisson GMM results of value-added related variable for OECD members + China (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	30.375***			5.778***			25.203***		
	(2.320)			(0.694)			(2.060)		
log_dvaffd		31.894***			6.762***			26.148***	
		(2.570)			(0.776)			(2.237)	
log_ova			27.011***			5.615***			22.220***
			(2.322)			(0.703)			(2.028)
log_TP_i	20.066***	19.651***	23.612***	3.124***	2.872***	3.611***	17.057***	16.828***	19.979***
	(1.233)	(1.239)	(1.378)	(0.425)	(0.421)	(0.467)	(1.109)	(1.115)	(1.231)
log_TP_j	18.792***	18.383***	21.716***	2.820***	2.484***	2.986***	16.206***	16.033***	18.747***
	(0.961)	(0.977)	(1.134)	(0.332)	(0.320)	(0.388)	(0.864)	(0.880)	(1.021)
DIS_ij	-4.303***	-7.131***	-7.633***	-0.413	-0.659**	-0.832**	-3.703***	-6.204***	-6.459***
	(1.197)	(1.089)	(1.266)	(0.332)	(0.320)	(0.350)	(1.070)	(0.966)	(1.122)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	42.712***	45.418***	53.222***	6.982***	7.332***	8.725***	35.861***	38.265***	44.669***
	(2.188)	(2.306)	(2.568)	(0.545)	(0.584)	(0.684)	(1.913)	(2.009)	(2.212)
GVCPi	-0.764	-5.111**	6.632***	1.128	0.230	2.115***	-1.688	-5.165***	4.712**
	(2.198)	(2.176)	(2.125)	(0.813)	(0.782)	(0.745)	(1.979)	(1.961)	(1.896)
GVCPj	4.816	1.031	16.881***	2.293***	1.633**	4.857***	2.769	-0.268	12.651***
	(3.207)	(3.358)	(3.671)	(0.718)	(0.699)	(0.902)	(2.843)	(2.963)	(3.232)
log_GDP_i	14.285***	13.691***	12.085***	3.079***	3.288***	2.780***	12.125***	11.549***	10.175***
	(2.337)	(2.367)	(2.348)	(0.816)	(0.818)	(0.780)	(2.080)	(2.089)	(2.081)
log_GDP_j	24.603***	28.393***	22.631***	0.444	1.122	0.389	22.862***	25.797***	21.013***
	(3.823)	(3.981)	(3.903)	(0.837)	(0.855)	(0.895)	(3.391)	(3.518)	(3.465)
Observations	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324

Robust z-statistics in parentheses

∗ ∗ ∗p<0.01, ∗∗p<0.05, ∗p<0.1

Table 3.10: IV Poisson GMM results of exports related variable for OECD members + China (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	32.675***			5.817***			27.272***		
	(2.374)			(0.671)			(2.126)		
log_Final		32.738***			5.851***			27.375***	
		(2.483)			(0.853)			(2.208)	
log_Bilateralexport			33.215***			5.887***			27.752***
			(2.406)			(0.726)			(2.156)
log_TP_i	19.671***	19.383***	19.254***	3.078***	3.035***	2.974***	16.546***	16.403***	16.272***
	(1.273)	(1.201)	(1.234)	(0.549)	(0.456)	(0.507)	(1.132)	(1.077)	(1.101)
log_TP_j	18.050***	17.936***	17.613***	2.535***	2.463***	2.431***	15.538***	15.552***	15.241***
	(1.026)	(0.897)	(0.945)	(0.381)	(0.294)	(0.340)	(0.927)	(0.811)	(0.854)
DIS_ij	-2.205*	-4.358***	-2.924**	-0.345	-0.626*	-0.408	-1.644	-3.576***	-2.326**
	(1.328)	(1.100)	(1.211)	(0.340)	(0.330)	(0.320)	(1.207)	(0.992)	(1.101)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	44.534***	42.426***	43.207***	7.261***	6.992***	7.051***	37.234***	35.529***	36.172***
	(2.328)	(2.298)	(2.259)	(0.606)	(0.544)	(0.559)	(2.018)	(2.007)	(1.971)
GVCPi	2.963	-1.098	0.760	0.977	0.668	0.741	1.955	-1.709	0.011
	(2.235)	(2.247)	(2.218)	(0.746)	(0.768)	(0.749)	(2.024)	(2.056)	(2.019)
GVCPj	11.163***	6.128*	9.226***	3.598***	2.834***	3.296***	7.848***	3.704	6.245**
	(3.256)	(3.374)	(3.294)	(0.765)	(0.654)	(0.704)	(2.902)	(2.990)	(2.932)
log_GDP_i	13.548***	12.497***	12.770***	2.931***	2.687**	2.783***	11.157***	10.400***	10.559***
	(2.454)	(2.605)	(2.473)	(1.043)	(1.087)	(1.055)	(2.170)	(2.312)	(2.190)
log_GDP_j	21.220***	25.543***	22.340***	0.376	0.683	0.323	20.025***	23.759***	21.053***
	(3.777)	(4.003)	(3.869)	(1.004)	(0.852)	(0.918)	(3.376)	(3.565)	(3.457)
Observations	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table 3.11: IV Poisson GMM results of value-added related variable for OECD members + China (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	32.617***			5.920***			27.195***		
	(2.365)			(0.697)			(2.112)		
log_dvaffd		34.399***			6.814***			28.428***	
		(2.650)			(0.778)			(2.319)	
log_ova_ij			29.594***			5.357***			24.706***
			(2.263)			(0.641)			(2.011)
log_TP_i	18.411***	17.720***	21.815***	2.818***	2.561***	3.341***	15.580***	15.128***	18.362***
	(1.169)	(1.156)	(1.258)	(0.486)	(0.476)	(0.492)	(1.048)	(1.038)	(1.126)
log_TP_j	17.387***	16.823***	20.135***	2.363***	2.069***	2.706***	15.059***	14.731***	17.339***
	(0.934)	(0.945)	(1.076)	(0.332)	(0.328)	(0.359)	(0.845)	(0.851)	(0.970)
DIS_ij	-3.047**	-5.847***	-6.078***	-0.366	-0.602*	-0.903***	-2.460**	-4.959***	-4.891***
	(1.198)	(1.096)	(1.223)	(0.310)	(0.308)	(0.321)	(1.086)	(0.980)	(1.100)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	41.287***	43.870***	52.006***	6.694***	7.090***	8.335***	34.593***	36.875***	43.601***
	(2.148)	(2.305)	(2.542)	(0.538)	(0.569)	(0.661)	(1.878)	(2.004)	(2.191)
GVCPi	-1.968	-6.692***	5.730***	0.296	-0.564	1.632**	-2.306	-6.252***	4.088**
	(2.246)	(2.245)	(2.110)	(0.758)	(0.756)	(0.705)	(2.041)	(2.025)	(1.897)
GVCPj	4.309	-0.305	16.719***	2.422***	1.690**	4.546***	2.170	-1.592	12.533***
	(3.080)	(3.316)	(3.587)	(0.681)	(0.666)	(0.833)	(2.751)	(2.946)	(3.187)
log_GDP_i	12.944***	12.118***	10.247***	2.824***	2.949***	2.286**	10.709***	9.982***	8.480***
	(2.440)	(2.521)	(2.425)	(1.016)	(1.001)	(0.936)	(2.165)	(2.223)	(2.155)
log_GDP_j	22.872***	27.079***	20.872***	0.444	0.868	0.598	21.442***	24.874***	19.580***
	(3.752)	(4.081)	(3.798)	(0.911)	(0.904)	(0.953)	(3.354)	(3.623)	(3.402)
Observations	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324	9,324

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

3.7 Conclusion and Policy Complications

In this paper we explore the relationship between of GVCs and international technological collaboration with a focus on collaborative eco-innovation at the country level. Estimating a PPML with three-way fixed effects, we find clear links between trade and collaborative innovation and collaborative EI. Our results show that geographical proximity and cultural proximity have a significant impact on Collaborative EI. Economic size and domestic research ability are also shown to stimulate technological collaboration (Picci, 2010; Montobbio and Sterzi, 2013).

Our results show that a country's position in a GVC may affect collaborative EI. Global value chains include the top (upstream) of the value chain (knowledge innovation link), the middle of the value chain (the application of new technology to produce new products) and the bottom (downstream) of the value chain (product sales and after-sales). Countries in the middle and upstream cooperate as suppliers by providing each other with their DVA for further processing and the export. During this process, technology is transferred through GVCs with the flow of DVA from one country to the other.

Our results show that trade in intermediate products, final products, total bilateral exports and exports in DVA through GVCs stimulate collaborative EI, although the magnitudes differ. Comparing the results with and without the largest trade partners, we find that the time it takes for trade to stimulate collaborative innovation can vary and that newly industrialising countries such as China are playing a more important role in GVCs and are increasingly help stimulate collaborative EI.

A wide range of policies have been used to stimulate international technological collaboration.

However, because of the complex global trading network, traditional methods such as increasing subsidies for R&D or strengthening the Intellectually Property Rights (IPR) protection system now need international cooperation (OECD, 2017). Policies aimed at stimulating collaborative EI should be formulated at a global level. More specifically, policymakers need to take into account that developing countries are not only the source of raw materials but also where much of the production takes place and are the countries that would benefit the most from an increase in collaborative EI through the GVCs. For example, for some developing countries such as Brazil, Indonesia and South Africa, their relatively weak domestic innovation capabilities (Bell, 2009; Bell, 2012; Manda and Ben Dhaou, 2019), slow industrial upgrading (Manda and Ben Dhaou, 2019; R. Lema and Rabellotti, 2023) and unsound patent protection systems (Peng et al., 2017), means that it is difficult for them to develop green technologies independently and why developed countries tend to dominate green technology development (Barbieri, Marzucchi, and Rizzo, 2020). As Corrocher and Mancusi (2021) state, the ability of BRICS countries (Brazil, Russia, India, Indonesia, China, and South Africa) to partake in international collaborative patenting initiatives is constrained and underscores the importance of joint R&D programmes between developed and developing countries to help develop new technologies. Our paper shows that the cooperation along the GVCs offers a channel to promote cooperation in green technological development for both developing countries and developed countries.

Chapter 4

Patent Quality and the International Diffusion of Green Technologies: The role of Co-Innovation

4.1 Introduction

A high-quality patent is often associated with the potential economic profits of companies (Squicciarini, Dernis, and C. Criscuolo, 2013). From a company's perspective, patent quality is often assessed in the context of issues related to corporate innovation policies, R&D investments and firm performance, among other financial concerns (Schot and Steinmueller, 2018). The prospect of financial gain incentivises companies to innovate, as they anticipate that a high-quality patent will help them to achieve higher profits, greater recognition, or additional subsidies (Hall, 2019). However, the impact of high-quality patents is often not limited to profits alone. Different stakeholders have different interpretations of what constitutes 'high quality'. For economists, a good invention is one that can provide effective guidance for future technologies, facilitate knowledge exchange, and even upgrade an industry through technology diffusion (Bessen, 2008). In this study, we use the economists' definition of a "good" patent or innovation, which is one that has a favourable effect on the release of technology in the future. Patent forward citation is one of the important indicators to measure patent quality and knowledge spillover effects. It refers to the situation where other patents cite a granted patent as a technical reference in subsequent applications (Sorenson and Fleming, 2004). Forward citations can reflect the quality of a technology, and also indicate the influence of the technology on the development of subsequent technologies, that is, to measure the knowledge spillover effects (Squicciarini, Dernis, and C. Criscuolo, 2013). Observing the publication locations of forward-citing patents can measure the global knowledge diffusion effects of the cited patent(D. B. Audretsch and Feldman, 2004).[1]

More specifically, we are interested in the quality of patents associated with eco-innovations. Eco-innovation has gained recognition for its beneficial impacts on economic production and employment as well as being a crucial tool for solving environmental issues like pollution and climate change (Arbolino et al., 2018). However, eco-innovation often requires funding and R&D costs, emphasising the importance of collaboration (Antoine Dechezleprêtre, Martin, and Bassi, 2019). Global technological cooperation is considered a critical method for promoting eco-innovation and facilitating the diffusion and transfer of green technologies (Duan, Nie, and Coakes, 2010; D. B. Audretsch, Lehmann, and Wright, 2014). Collaboration plays a pivotal role in stimulating knowledge spillovers, which are the unintentional dissemination of knowledge and skills from one person, firm, or sector to another. Collaboration brings together individuals

[1]Forward citations refer to the subsequent patents that cite a given patent, while forward citation counts quantify a patent's knowledge spillover effects based solely on the number of times it is cited. Forward citation data is widely used to measure an invention's quality, with counts being the most common method employed. However, this approach does not differentiate between internal and external knowledge spillovers, which is a significant limitation in assessing the true impact of a technology. Therefore, building upon the foundation of forward citation data, this paper develops a new methodology to measure technology impact more accurately.

or organisations with different expertise, backgrounds, and perspectives. This amalgamation of diverse thoughts leads to the interchange of knowledge, which can then be absorbed and utilised by all participating entities. The significance of promoting efficient diffusion of green technologies between developed and developing countries is underscored by an analysis of the recent increase in global emissions, which indicates that the majority of this growth emanates from developing countries.(Copeland, 2021). Encouraging collaboration and innovation between these two groups can help to reinforce knowledge sharing, thereby mitigating pollution concerns. Our paper is motivated by the growing need to address global environmental challenges through knowledge diffusion from eco-innovation and global technological collaboration. This paper aims to analyse the quality of eco-innovation and global technological collaboration innovation, especially the role of guiding future technologies, and the effects of cross-border knowledge sharing.

This paper offers three primary contributions to the existing literature. First, our research builds upon a well-established tradition in the literature and devises novel measures of cross-border knowledge spillovers based on patent citation data. In addition to traditional metrics such as forward citation counts for assessing patent quality and knowledge spillover effects, we have developed a new measure based on forward citations combined with the Herfindahl-Hirschman Index (HHI). This approach addresses the limitations of forward citation counts, which fail to distinguish between internal and external knowledge diffusion (Grossman and Helpman, 1991; A. B. Jaffe, Trajtenberg, and Henderson, 1993; D. B. Audretsch and Feldman, 2004). By adopting a citation analysis technique that considers the country of origin of the forward citations and constructing a citation concentration index, we could effectively identify cross-border knowledge spillovers that may not be entirely captured by conventional measures.

Second, to the best of our knowledge, this study represents the first attempt to examine whether eco-innovation plays a more significant guiding role in shaping future technologies and can enhance cross-border technological diffusion when compared to non-eco innovation. Several studies have established that eco-innovation exhibits stronger technological diffusion than non-eco innovation. For example, René Kemp and Volpi (2008) and Foxon and Pearson (2008) conclude that clean technology diffusion is driven by both endogenous and exogenous factors and that policy plays a role but is not the only important factor. Antoine Dechezleprêtre, Martin, and Mohnen (2013) analyses patent citation data to compare knowledge spillovers in clean and dirty technologies across four technological fields, finding that clean patents received 43% more citations and were cited by more prominent patents due to their general applications and radical newness. However, these studies didn't show evidence about distinguishing the internal and external knowledge spillover effects, and our paper makes the first step.

Third, this paper also makes a significant contribution to the literature by investigating the quality of patents resulting from global collaborative innovation and its impact on cross-border knowledge spillovers. The prior literature has emphasised the importance of collaboration for innovation. Nieto and Lluís Santamaría (2010) examines the impact of technological collaboration on the innovation performance of small and medium-sized enterprises in comparison to larger firms. The results suggest that technological collaboration is crucial for smaller firms to improve their innovativeness. In addition, a large number of studies has examined the geographic effects of technology spillovers and the determinants of such spillovers through the use of forward patent citation counts. The previous literature suggests that domestic patents are more likely to be cited domestically (A. B. Jaffe, Trajtenberg, and Henderson, 1993), but the computer sector and technological leaders have more international knowledge flows (Peri, 2005). However, we did not find any research on the cross-border diffusion of knowledge and the quality in the context of global collaborative innovation.

Our analysis is conducted using patent data from the PATSTAT database. we have directed our focus towards inventions that were first published in the United States between the years 2001 and 2017, giving us more than two million observations.[2] Focusing on the inventions first published at the same patent office could mitigate the bias that different patent offices may have different examination regulation (Squicciarini, Dernis, and C. Criscuolo, 2013). The decision to focus on patents first published in the Unites States is rooted in the fact that American inventors play a significant role in the development of technologies. According to chapter 2, American inventors dominate with a 9% share of the world's total eco-innovations, positioning the United States at the top of the rankings. Whether it is eco-innovation or collaborative innovation, the United States remains the primary contributor, as evidenced by the largest share of inventions originating from within its borders. Furthermore, the US Patent Office has maintained its status as the leading office for global patent filings for an extended period WIPO. (2020). And it is worth noting that the United States also holds a crucial role as the primary innovation partner for countries that actively collaborate. Moreover, we utilise the forward citation data of a patent family as a measure to assess the quality of innovation. We also calculate the concentration index of forward citations based on quantifying the total count of countries from which the forward citations originate to measure cross-border knowledge spillover effects. By calculating the number of times a technology is cited by other technologies, we can assess the quality of the cited invention, and the geographical distribution of these forward citations can depict the global knowledge flow of the cited technology (A. B. Jaffe, Trajtenberg, and Henderson, 1993).

[2]The earliest application year was between 2000 and 2016.

In summary, our study indicates that eco-innovation is more effective in stimulating future technologies and generating larger cross-border knowledge spillover effects (Antoine Dechezleprêtre, Martin, and Mohnen, 2013; Antoine Dechezleprêtre, Muckley, and Neelakantan, 2021). Based on our analysis, eco-innovation has the potential to generate about 5% higher forward citation index compared to non-eco innovation, all other factors being equal. Our research also reveals compelling evidence of larger cross-border spillover effects from eco-innovation compared to non-eco innovation. The citation counts of technologies are often related to knowledge spillovers. Specifically, we have found that eco-innovation has a greater potential to diffuse to more countries, and its concentration index is lower, indicating that eco-innovation has better impact in stimulating future innovation (The magnitude of these effects may differ across various technology fields). Additionally, we have also found that overall technologies resulting from collaborative efforts between researchers from different countries tend to have higher forward citation index, suggesting a stronger technological guidance effect compared to non-collaborative innovation although we find mixed results across different technology fields.

Our results have also revealed that various patent characteristics, such as patent scope, backward citations, patent family size, and the number of researchers involved in the R&D process, as well as the time duration between application and publication, are related to the quality of patents and the cross-border diffusion of technologies. Specifically, patent families with a higher number of backward citations, larger patent family size, and more researchers involved in the R&D process tend to have higher quality and stronger technological guidance for future innovations, while also facilitating the geographical diffusion of knowledge. However, a longer duration between application and publication is associated with lower patent quality and a lower scope for global knowledge diffusion. This is because important technologies are more likely to be reviewed and published faster through the patent application process (Harhoff and S. Wagner, 2009; Régibeau and Rockett, 2010), and patent applicants may try to expedite the review process for potentially more valuable patents by well documenting their application documents (Squicciarini, Dernis, and C. Criscuolo, 2013).

The paper is structured as follows. Section two outlines the theoretical and empirical foundations that underpin the analysis presented in this study. Section three provides a detailed description of the data sources and variables used in the analysis, including our method of distinguishing between eco and non-eco technologies and our approach to defining global technological collaboration from an innovation perspective. In section four, we present our database and describe our data. Section five provides a comprehensive discussion of the empirical methodology employed in this study. In section six, we estimate the quality and diffusion of collaboration innovation and eco-innovation. Finally, section seven concludes the paper by discussing the implications of our results.

4.2 Literature Review

Our research is connected to three strands of the literature. Firstly, we have built upon the vast empirical research that has utilised patent data to examine both the quality of technologies and their knowledge spillover. Secondly, our research begins with the established concept that eco-innovations diffuse more extensively than non-eco innovations, particularly in certain types of technology. Thirdly, our study is closely related to the literature that identifies collaboration and geographically knowledge diffusion as crucial drivers of innovation and economic growth.

4.2.1 Patent quality and knowledge spillovers

The term 'patent quality' encompasses different meanings and interpretations, which depend on the stakeholders and situations. According to a discussion in a WIPO Magazine, when people refer to 'a good patent', they may emphasise that the patent has exclusionary power or relative economic value to the patent owner (Berman, 2005).[3] That is so-called 'validity' (Berman, 2005) and there is a difference between the terms 'quality' and 'validity'. Every patent may have the ability to protect the intellectual property right of the patent owner if the patent application document is well-drafted and the scope of the inventions' protection is will-claimed (Squicciarini, Dernis, and C. Criscuolo, 2013). However, a 'valid' patent does not necessarily mean it may generate value for the patent owner or future innovations. From an economics perspective, 'good quality' indicates that the invention has a guiding impact on future technological development and could stimulate innovation by knowledge sharing (Guellec and La Potterie, 2007; Squicciarini, Dernis, and C. Criscuolo, 2013). This is the definition of quality that we adopt in this paper.

Knowledge spillovers, commonly defined as the "external benefits of creating knowledge accumulated by others than the creators" (Agarwal, D. Audretsch, and Sarkar, 2010:p.271) are crucial drivers of innovation, economic growth, and societal progress (D. B. Audretsch and Keilbach, 2008). The term 'knowledge spillovers' refers to the procedure by which external knowledge sources produced outside of a particular unit, such as a company or region, are gathered, incorporated, and applied within one's own creative processes (Aldieri, Makkonen, and Vinci, 2020). Externalities associated with knowledge spillovers can be positive or negative. On the one hand, they can quicken the spread of innovation, which will benefit several sectors and geographical

[3]Exclusionary power means that the patent could effectively exclude others from practising the invention without the patent owner's permission (Berman, 2005).

areas (Peres, Muller, and Mahajan, 2010; M. Xu, David, Kim, et al., 2018). However, they can also lead to free-riding incentives and possible crowding effects in R&D efforts, as some businesses may try to profit from the knowledge created by others without making significant expenditures in their own R&D (Aldieri, Carlucci, et al., 2019).

In order to study the effects of innovation and develop policies that incentives innovation, it is researched from various perspectives such as geographical, technological, and organisational dimensions. However, quantifying the impact of innovation poses a significant challenge due to the considerable variation in characteristics among different technologies (Fleming, 2007). Patent data has been an essential indicator of measuring knowledge spillovers and the geographic distribution of innovation (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017). Patent data can help identify flow knowledge diffusion through innovative activities and therefore to analyse the relationships between inventors and geographic distribution of innovation (C. Chen and Hicks, 2004; Baruffaldi and Simeth, 2020).

Although, patent data cannot directly capture knowledge spillover effects or economic value (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017), simple patent families and citation counts go a good way in alleviating those shortcomings. A simple patent family refers to a collection of patent documents that are related to a single invention, filed in multiple jurisdictions (countries or regions) to obtain patent protection for the same technology (Martinez, 2010). The simple patent family concept is based on the priority patent application document, which is the first filed patent that serves as the basis for claiming priority in subsequent patents (Martinez, 2010). Essentially, a patent family is a set of patents that cover the same technical content, so focusing on the patent family level will avoid the double counting invention problem (Dernis and M. Khan, 2004) and it has been widely applied when measuring international diffusion of knowledge (C. Chen and Hicks, 2004; Duan, Nie, and Coakes, 2010).

Forward citations refer to the citations a particular patent has received from subsequently filed patents as prior art (Brinn et al., 2003). It is used as an effective indicator of the importance and impact of an invention on future technologies. By calculating the forward citation counts of a simple patent family, we could measure the knowledge diffusion of technologies; the more forward citations a patent family has, the more influential and valuable it is considered to contribute new inventions.[4] Forward citations are often considered a good measure of patent quality due to their ability to capture an invention's possible impact on future innovations.

In addition to forward citations metric which emphasise the knowledge spillover of an invention, several additional factors are associated with patent quality. One variable is the number of backward citations, which refers to the number of prior patents, non-patent literature and other sources of knowledge listed in a patent application document (Hall, A. Jaffe, and Trajtenberg, 2005; Squicciarini, Dernis, and C. Criscuolo, 2013). Harhoff, Scherer, and Vopel (2003) found that both patents related backward citation and non-patent related citations are positively correlated with patent value. However, Fadavi Hoseini and Mansouri (2022) found that for nanotechnology, new innovation are more technology-driven, with only 36% of patent's backward citations being non-patent references, which proves that patent backward citations and non-patent backward citations have different magnitude effects in stimulating future innovation (Harhoff, Scherer, and Vopel, 2003). Moreover, given that backward citations reflect the level

[4] A simple patent family may have more than one patent family member which could be cited by other patents that belong to other patent families. When calculating forward citations at the patent family level, the forward citations are calculated as the total number of distinct patent families where the citing patents belong. By aggregating the forward citations received by all patents within a patent family over five years after the publication date, we could provide a more accurate and comprehensive measure of an invention's impact on subsequent innovations (Brinn et al., 2003). We also consider the self-citation problem. Details will be explained in the next section.

of prior knowledge that the invention builds upon, during the technical procedure, the patent applicants are required by the patent examiners to list any prior knowledge that the patent used as reference (Alcácer, Gittelman, and Sampat, 2009). Any irreverent citations will be removed by examiners, which distinguish the backward citations as applicant citations and examiner citations (Alcácer, Gittelman, and Sampat, 2009). Backward citations are highly associated with the 'patentability' of an invention regardless of whether these are added by the applicants or the examiners (Haščič and Migotto, 2015b). P. Criscuolo and Verspagen (2008) investigates whether patent citations can serve as reliable indicators of technology flows by analysing the difference between citations added by inventors and patent examiners. Using European Patent Office (EPO) data, the authors reveal that geographical factors are the main determinant of influencing citing behaviour. Higham, De Rassenfosse, and A. B. Jaffe (2021) reveal a strong correlation between the number of applicant citations and examiner citations, suggesting that the technology's nature drives both sets of citations higher concurrently, with patents having many applicant citations typically also having many examiner citations.

The patent scope, referring to the breath of technological content covered by a patent, has a strong connection to both its technological significance and its economic value (Squicciarini, Dernis, and C. Criscuolo, 2013). Patent scope is often determined by counting the unique International Patent Classification (IPC) codes found in patent documents (Squicciarini, Dernis, and C. Criscuolo, 2013). However, having more codes does not necessarily imply a broader scope for the invention, unless it can be classified into multiple distinct technological fields.[5] Numerous studies have demonstrated that the technological scope of inventions is valuable to firms and has a significant impact on their performance (Makri, Hitt, and Lane, 2010; Agostini et al.,

[5]The IPC system is a method for categorising innovations into various technological fields based on their technical content. A detailed explanation of this classification system will be provided in the following section.

2015; Tahmooresnejad and Beaudry, 2019). Furthermore, a broader scope is often indicative of greater potential technological value for an invention (A. B. Jaffe, 2000; Tahmooresnejad and Beaudry, 2019; Noh and S. Lee, 2020).

The size if a patent family, defined as the number of patents under which a specific invention is protected, has also been shown to be correlated with patent quality. Harhoff, Scherer, and Vopel (2003) found that large international patent families are particularly valuable, suggesting that the more extensive the geographic protection, the higher the perceived value of the invention. Antoine Dechezleprêtre, Ménière, and Mohnen (2017) and Danish, Ranjan, and Sharma (2020) conducted a comprehensive analysis of international patent family characteristics and found that patent scope, patent family size, backward citations and number of inventors are all positively associated with patent value. The literature also highlights that the time span between the application and publication within a family can also serve as valuable indicators of the worth of patented innovations. Harhoff and S. Wagner (2009) and Régibeau and Rockett (2010) found a negative relationship between the value of a patent and the time span between the application date and publication date. A potential explanation is that valued patents may be issued quickly as those patents are well documented (Harhoff and S. Wagner, 2009; Danish, Ranjan, and Sharma, 2020).

4.2.2 Knowledge spillovers from eco-innovation

René Kemp and Pearson (2007) define eco-innovation, also known as environmental or green innovation, as the development and implementation of new products, processes, technologies, or organisational methods that contribute to the reduction of environmental impacts, resource depletion, and pollution, while also promoting economic growth and social welfare. Incentivising eco-innovation has become an important part of the United Nations 2030 Sustainable Development Goals (Cf, 2015; R. Wang, J. Tan, and Yao, 2021), in the aim to reduce the negative impact of production on the environment while ensuring economic growth (Makkonen and Inkinen, 2021). Puertas and Marti (2021) examine the determinants of greenhouse gas emissions in OECD countries from 2011 to 2018, revealing that eco-innovation, CO2 productivity, and environmental policies significantly contribute to emission mitigation. Besides, there is also a close relationship between eco-innovation and firm performance. Enterprises' investment in green R&D can not only alleviate environmental pollution problems, but also bring benefits to enterprises (CARRILLO, KÖNNÖLÄ, et al., 2009).

The literature shows that improving technological capabilities through R&D, environmental regulations, environmental management tools, and organisational changes all stimulate environmental innovation(Horbach, 2008). Demirel and Kesidou (2011) examine the role of external policy tools and internal firm-specific factors in stimulating eco-innovations and show that efficiency improvements and environmental regulations are key drivers for eco-innovation. Fernando and Wah (2017) build a theoretical framework designed to evaluate the influence of five eco-innovation factors on environmental performance, utilising survey data from Malaysian green technology firms. The results reveal that adherence to environmental regulations, emphasis on market needs, and the implementation of suitable technology are crucial determinants of enhanced environmental performance. The literature also suggests that eco-innovation allows businesses to tackle competitive obstacles and strengthen their market standing. Cai and G. Li (2018) also identify factors like technological capabilities, environmental organisational capabilities, market-based instruments, competitive pressures, and customer green demand as significant contributors to eco-innovation which could enhance environmental performance.

These findings align with the Porter Hypothesis, which postulates that such factors encourage eco-innovative efforts (Ambec and Barla, 2002).

In recent years, many researchers have conducted in-depth studies on the impact of eco-innovation and knowledge spillover effects in achieving sustainable development and stimulating economic growth. Eco-innovation is a key strategy that can achieve the dual benefits of environmental and economic goals, by reducing resource consumption and environmental pollution in the production process, thereby increasing production efficiency (Makkonen and Inkinen, 2021). At the same time, knowledge spillover effects play a key role in innovation activities, and the interaction between firms can enhance innovation capabilities and thus promote economic growth (Cainelli, Mazzanti, and Zoboli, 2011). Knowledge spillovers help to increase the overall level of innovation and thus have a positive impact on economic growth. Therefore, policymakers should focus on encouraging R&D investment and promoting knowledge spillovers to achieve sustainable development and economic growth.

Aldieri (2011) examines the effects of technological and geographic proximity on knowledge spillovers. By analysing US patent citation data, the authors find that knowledge spillovers are more likely when firms are technologically and geographically closer. Furthermore, the article reveals the importance of knowledge spillovers, emphasising its role in driving innovation and economic growth. The conclusions also emphasise that policymakers should focus on supporting collaboration between technologically and geographically close firms to facilitate knowledge spillovers and innovation. On this basis, Crescenzi, Nathan, and Rodríguez-Pose (2016) further examine the characteristics of collaboration among inventors in the United Kingdom (UK) by examining the types of geographic, organisational, cognitive, social and cultural-ethnic proximity that prevail between inventors in partnerships that ultimately lead to technological progress. The study also highlights the key role of knowledge spillovers in eco-innovation and sustainable development by suggesting that innovation policies should promote the formation of open and diverse inventor networks. Hájek and Stejskal (2018) analyses the impact of R&D collaboration and knowledge spillovers on sustainable business innovation in the chemical industry by exploring the origin of knowledge spillovers from collaborations between companies, universities, and R&D organisations. The authors find that the knowledge acuqired from companies internal source could increase innovation and sustainable performance. They also find that firm collaborations with universities and other firms promote different types of knowledge spillovers and may influence multiple modes of sustainable activity in innovation.

Furthermore, Aldieri, Makkonen, and Vinci (2020) analyse the role of green knowledge spillovers in promoting firms' technological efficiency by focusing on Europe, Japan, and the United States during the period 2002-2017. By comparing Europe, Japan, and the United States, the findings show that while green knowledge spillovers have a significant and positive impact on firm productivity, technological diversity increases the technical efficiency of Japanese and European firms but decreases that of American firms. H. Sun et al. (2021) investigate the impact of technological innovation in certain countries on the energy efficiency performance of neighbouring countries. Using data from 24 innovative countries between 1994 and 2013, the findings show a positive relationship between country-specific knowledge spillovers and energy efficiency performance. This is reflected in the steady improvement in energy efficiency in countries like Germany, France, the United Kingdom, the Netherlands and Switzerland which have the highest energy efficiency. Aldieri and Vinci (2020) examine the role of knowledge spillover in clean production-related fields, specifically in the energy sector. By analysing data from the United States, Japan, France, Belgium, Germany, Sweden, Italy, the Netherlands, the United Kingdom, Finland, and Denmark between 2002 and 2014, the research highlighted the significant impact of green knowledge spillover effects in addressing climate change on business productivity. It also emphasised the importance of policies in facilitating this process. By categorising knowledge spillovers as eco and non-eco, Aldieri, Makkonen, and Vinci (2022) explores the extent to which R&D and environmental knowledge spillovers contribute to the achievement of the United Nations (UN) Sustainable Development Goals (SDGs). The analysis is based on data from the European Union, Japan, and the United States between 2002 and 2017. The findings reveal that while R&D is generally not helpful in realising the objectives outlined in SDGs, environmental knowledge spillovers can facilitate their attainment. These outcomes also endorse the perspective that policymakers should not support all R&D (both eco and non-eco), but instead design policies that specifically encourage eco-innovation and green knowledge spillovers.

4.2.3 Collaboration and geographical knowledge spillovers

According to the literature, collaborative innovation is the creation of new values through cooperation (S. M. Lee, Olson, and Trimi, 2012) and refers to the joint efforts of multiple parties with different characteristics and resources to develop new technologies or upgrade existing technologies (Saragih and J. D. Tan, 2018). Collaborative innovation can occur between countries, companies, universities and individuals. De Prato and Nepelski (2014) explain that international technical collaboration (international collaborative innovation) is the outcome of the segmentation of the invention process on a global scale, in which inventors from other countries interact and are able to combine information and knowledge from various sources (Sachwald, 2008).[6]

[6] The international division of innovation, also called innovation internationalisation, means that the innovation process of inventing a new 'general-purpose technology' (such as biotechnology and new materials) is subdivided and finished by inventors located in different countries (Archibugi and Iammarino, 2002).

During this process, inventors seek opportunities to collaborate worldwide, strengthening the knowledge flow between countries at an aggregate level. Essentially, international technological collaboration is a form of innovation internationalisation (Archibugi and Iammarino, 2002; De Prato and Nepelski, 2014). Following the existing literature, we define international technological collaboration (international collaborative innovation) as the invention of new technologies and breakthroughs derived from the cooperation between inventors who reside in different countries.

In recent years, there has been a major increase in the number of studies on knowledge spillovers, with a special emphasis on collaboration networks and geographic spillovers. By comparing the key factors of R&D cooperation between domestic and foreign innovative companies and public knowledge institutions in Finland and the Netherlands, Van Beers, Berghäll, and Poot (2008) find that incoming knowledge spillovers are very important for R&D cooperation in both countries. At the same time, the research results show the important role of innovation policies in stimulating domestic enterprises to cooperate with enterprises and knowledge institutions in other countries, which shows that different countries have different policies in stimulating R&D cooperation. For example, Finnish companies are more willing to share knowledge with public R&D partners than Dutch companies. Lööf (2009) also examines the impact of domestic and foreign R&D collaborations on knowledge spillovers using Swedish multinational enterprises (MNEs) data, and posit that knowledge spillovers from R&D collaborations are usually a network phenomenon rather than a process between a local firm and a single innovation partner. They also find that successful cooperation depends on the existence of foreign innovation partners in the network, and cooperative innovation between countries often has an impact on the innovation of other partners in the network. In their 2009 investigation into the significance of social networks in promoting knowledge spillovers, by analysing large amounts of patent data and regional economic data, Breschi and Lissoni (2009) explores the link between labour mobility and innovation. Using network analysis, the study finds that the flow of skilled workers makes a great contribution to the generation of innovative ideas and promotes the formation of local collaborative innovation networks. The study also highlights the importance of distance for knowledge exchange and collaboration between inventors. These findings suggest that policy-makers should encourage skilled labour mobility and foster the development of local innovation ecosystems to enhance regional knowledge flows and overall economic growth.

By analysing more than 700 firms, Montoro-Sánchez, Ortiz-de-Urbina-Criado, and Mora-Valentín (2011) suggest that knowledge spillovers have a positive impact on firms' propensity to innovate and the likelihood of firms participating in inter-organisational R&D collaborations. Through an in-depth study of pharmaceutical industry data, M. Zhao and Islam (2017) highlight the important impact of partners' R&D capabilities on innovation. First, the additional spillover effects of cross-regional cooperation may be reduced if the cooperation is mainly carried out within large firms. This is because R&D resources within large companies may be concentrated in specific regions, limiting the potential for cross-regional collaboration (M. Zhao and Islam, 2017). Second, regions with higher levels of inter-regional cooperation tend to produce more valuable technologies, which also prove the idea from Uyarra, Sörvik, and Midtkandal (2014). This is because cross-regional cooperation can promote the exchange of knowledge and skills, thereby improving the overall R&D level (Aslam et al., 2018). By sharing information and experience with partners in different regions, firms can better respond to challenges and improve innovation capabilities, which can also promote industrial cluster effects and attract more talents and funds into the field of R&D (Sørensen and Torfing, 2011). By examining firm-level R&D

and knowledge spillovers and using data from 9,213 UK firms, D. B. Audretsch and Belitski (2020) aims to assess the extent to which knowledge spillovers complement innovation and firm productivity. The findings indicate that R&D is important for both innovation and productivity, while knowledge spillovers have a more significant impact on firm productivity than R&D.

Qiu, X. Liu, and Gao (2017) analyse the effect of different cooperation methods on innovation for different countries or regions. International cooperation, especially with developed countries with cutting-edge knowledge, is considered to be an effective way to promote innovation in developing countries (Archibugi and Pietrobelli, 2003; Qiu, X. Liu, and Gao, 2017). This is because developed countries have great advantages in technological innovation, R&D capabilities and capital, and can provide strong support to developing countries (Lederman and Maloney, 2003). For developed countries, establishing research partnerships with local and global partners can effectively promote local innovation (Syed et al., 2012). Such collaborations can enhance knowledge transfer and improve research quality, while also helping to attract talented people and funding (Singh, 2005). However, for developing countries, more attention should be paid to local technical needs and actual conditions, rather than blindly pursuing international cooperation (Qiu, X. Liu, and Gao, 2017). This is because too much emphasis on international cooperation may lead to resource misallocation and fail to address actual local needs (Qiu, X. Liu, and Gao, 2017).

We know from past literature that a good patent can not only protect the rights and interests of the patent owner but also provide guidance for future inventions. There are many variables that can affect the quality of patents, and patent citation data is widely used to measure the effectiveness of existing technology on future inventions, that is, the knowledge spillover effect. At the same time, we learned that knowledge spillover effects and eco-innovation are not only beneficial for economic growth but also help to achieve sustainable development goals, and that collaboration is a powerful tool for stimulating innovation. Although existing literature has shown that green technologies have a stronger technology diffusion effect than non-green technologies, to the best of our knowledge, there is no literature that studies the technology diffusion of eco-innovations on a global scale, especially for each green technology field. Moreover, there are no articles discussing the impact of technologies developed through international technological collaboration on global future innovation. Our analysis aims to fill those gaps.

4.3 Data and Variables

4.3.1 Patent data

We use the simple patent family to represent innovations, which is collected from the PATSTAT database. As mentioned earlier, patent data is widely used to measure innovation. By using simple patent families, we can resolve the problem of double counting, since the connection between inventions does not depend on which member of the family, these family members represent the same invention (Acs, Anselin, and Varga, 2002). Patent documents do provide a wealth of information for research, including the classification of patents. According to the technical content of the patent, the patent family can be assigned to the corresponding technical field. Patents or patent families can be divided into 8 categories, namely, 'human necessities', 'performing operations and transportation', 'chemistry and metallurgy', 'textiles and paper', 'fixed construction', 'mechanical engineering (lighting, heating, etc.), weapons and explosives)', 'physics' and 'electrical engineering', according to the work from official documents of the World Intellectual Property Organisation (WIPO).[7]

[7]Examples of technologies in technical field could be found at the Appendix A.

Through the IPC codes, we can not only divide innovation into different fields, but also distinguish between eco and non-eco innovation. Environmentally Sound Technologies (ESTs), also called green technologies, are innovation that minimise ecological impacts and foster sustainable development across industries such as energy, waste management, agriculture, and water treatment (UNEP, n.d.). By reducing resource consumption, mitigating pollution, and strengthen ecosystem resilience, ESTs address urgent global challenges like climate change and biodiversity loss (Pasquali, 2018). For the research of eco-innovation, the first step is to subdivide green technologies in terms of different technical fields. Classifying green technologies can help policy makers and researchers better understand the status quo of technologies in various fields, so as to formulate corresponding development plans and policies and improve R&D efficiency. WIPO announced the 'IPC Green Inventory' in 2010. This project divides green technologies into seven categories by analysing the technical content contained in patent documents, namely 'alternative energy production', 'transportation', 'energy conservation', 'waste management', 'agriculture and forestry', 'administrative (regulatory) or design aspects' and 'nuclear power generation'.[8]

In addition to the classification of patents, patent documents also provide more useful information for research. First of all, patent documents contain patent application ID and simple patent family ID, which can help us classify similar patents into the same family and avoid double counting problems. Another important aspect is the filing date and grant date. By analysing a patent's filing date and grant date, we can determine the time it takes for the patent to be issued from the date of application, which can be used to evaluate the patent. Patents belonging to the same patent family claim the same earliest filing date. Patent documents also

[8]Examples of technologies in technical field could be found at the Appendix.

contain information about the applicants. The PATSTAT database divides applicants into six broad categories: government, university, corporation, non-profit organisation, hospital, and individual. Patent documents also contain inventor details such as name and address. The PATSTAT database goes a step further by assigning each inventor a unique ID. This allows us to track patents developed through cross-border collaborations. By looking at the country of residence of the inventor, we can identify which patents involve cross-border collaborations. When at least one member of a patent family is jointly developed by inventors from different countries, we consider this technology as an international technological collaborative innovation.

Patent documents also contain information about the knowledge to which the technology is referenced, which helps us understand forward and backward citations of patents. By analysing these data, we can explore the knowledge spillover effects of patents. At the same time, we have access to the residence country information of the inventors of forward citations, which allows us to study the diffusion effects of technologies on a global scale. In our research, we focus on patent families that were first published in the United States between 2001 and 2017.[9] We analyse the quality of different kinds of innovations and their impact on future technologies by counting the number of forward citations. At the same time, by analysing the source of forward citations, we can explore the international knowledge spillover effects. There are many reasons why we use innovation published after the year 2000. Since the year 2000, there have been numerous significant breakthroughs in the field of high-tech, such as the Internet, mobile communications, artificial intelligence, and biotechnology. The rapid development of these technologies has had a profound impact on patents. New inventions continue to emerge, driving a surge in patent applications. At the same time, there have been many changes in

[9] We have conducted an analysis of the cumulative number of forward citations within the initial five years following the publication of the patents. Consequently, the publication timeline is limited up to the year 2017.

patent laws and policies across countries, such as strengthening intellectual property protection, simplifying the patent application process, and improving patent quality (Abbott, Cottier, and Gurry, 2019). These changes may have influenced the quantity, quality, and value of innovation. Besides, the process of globalisation has accelerated since the beginning of the 21st century, and cooperation in innovation among multinational corporations has become increasingly close (Dicken, 2003). This may have led to changes in the composition, distribution, and value of patent families. Enterprises and research institutions are placing more emphasis on the strategic nature of patent portfolios, targeting key technology areas to ensure a competitive edge in future market competition (Somaya, 2012).

4.3.2 Variables

Dependent variables

A forward citation means that a patent is cited by other patents (Squicciarini, Dernis, and C. Criscuolo, 2013). The patent's technological significance for later-evolving technologies is captured by the forward citations (Hall, A. Jaffe, and Trajtenberg, 2005). Since family members represent the same innovation, forward citation analysis should always be consolidated at the patent family level. Combined with the inventor's information, we can exclude the case of self-citations to solve the problem of exaggerated knowledge spillover effects. Self-citations are when inventors cite their own previous patents. By identifying and excluding these citations, we can more accurately measure knowledge transfer and collaboration between different inventors.[10] The method we use to determine a patent family's total number of forward citations is

[10] Patent documents offer a wealth of information regarding the inventors associated with specific patent filings. The PATSTAT database allocates a unique identification number (ID) to each inventor. By correlating the ID of an inventor linked to a focal patent with inventor IDs associated with forward citations of that patent, it becomes feasible to identify forward citations that share a common inventor with the focal patent. Such forward citations with overlapping inventors are categorised as 'self-citations' and are subsequently excluded from the analysis. Beyond the exclusion of inventor self-citations, the methodology further allows for the identification of forward citations that share the same applicant as the focal patent, thereby enabling the exclusion of 'applicant self-citations' in the

shown in Figure 4.1. Let's assume that the numbers (1, 2, 3) represent the patent applications in various patent families, and the letters (A, B, C, D, and E) represent various patent families. The figure illustrates the three members of patent family A, each of which is cited in a number of subsequent patents belonging to other patent families. patents B1, D1, and E1, for instance, all reference patent A1. Additionally, we consider the country of residence where the inventors of forward citation are residing. The figure shows that the inventors of patents B1 and B2 are from France, whereas the inventors of patent D1 are from Japan.[11] Without considering the 'self-citation' problems, the sum of forward citations of the invention A is four (Four patent families cited invention A). However, if excluding 'self-citation', the answer is different. Self-citations mean that the inventors cite the technologies developed by themselves when they develop new technologies (Squicciarini, Dernis, and C. Criscuolo, 2013). Self-citations should be excluded when estimating the impact of an invention on subsequent inventions as self-citations do not cover knowledge spillovers among inventors (Squicciarini, Dernis, and C. Criscuolo, 2013). If we assume that C1 and patent family A have a common inventor, this would mean that patent C1 is the self-citation. When we calculate the total number of forward citations of invention A, we should not account for patent family C. Therefore the number of forward citations associated with invention A is three.

Forward citations, as an indicator of patent quality, have a truncation problem, because patents may continue to be cited for a long time, and the probability of recent patents being cited is relatively low (Hall, A. Jaffe, and Trajtenberg, 2005). To mitigate the impact of the truncation problem on the regression results, the literature suggests to only count forward citations within a five-year window from the date of patent publication (Hall, A. Jaffe, and Trajtenberg, 2005).

analytical framework.

[11]Figure 4.1 is a specific example, which assumes inventors of patent family B C D E are all from one specific country. In fact, inventors of each patent family may live in more than one country.

The number of forward citations of a patent family could be written as (Squicciarini, Dernis, and C. Criscuolo, 2013):

$$forward\_citation_{i,pi} = \sum_{t=p_i}^{P_i+5} \sum_{k \in K(t)} F_{k,i} \tag{4.1}$$

Where $forward\_citation_{i,pi}$ is the number of forward citations received by patent family i published at year pi, within 5 years after the publication dates. $F_{k,i}$ is the dummy that is equal to the one if patent family k cites patent family i and zero otherwise. $K(t)$ is the patent families published from the year t. It is worth noting that in different fields, the speed of technological development and forward citations may vary greatly. For example, in a fast-growing field (transportation), patents may be quickly cited and have a wide-ranging impact; whereas in mature or slower-growing fields (human necessities), patents may take longer to accumulate high citation counts. Therefore, direct comparisons of citation counts for inventions in different technological fields can be misleading. To solve this problem, we standardise the number of forward citations. Specifically, the number of forward citations per patent family can be divided by the maximum value of forward citations observed among patent families in the same technical field with the same earliest publication year (Squicciarini, Dernis, and C. Criscuolo, 2013). In this way, the obtained standardised forward citation value will be between 0 and 1, which can better reflect the relative influence of invention in various fields, and make cross-field comparisons more fair and accurate. The closer the value of the forward citation index is to 1, the better the quality of the invention and the stronger its technological spillover effect.

In addition to forward citations, We also study and quantify the international knowledge spillover effects of inventions. We construct a Forward Citation Concentration Index (FCI) to measure the geographic concentration of knowledge spillovers. In this way, it is possible to understand the extent to which these inventions have influenced the dissemination and exchange of knowledge between different countries, thereby assessing their global knowledge spillover effects. We exclude the United States, which allows us to measure the technical influence of an invention in the last five years on a global scale. We are inspired by Rhoades (1993)'s work on herfindahl-hirschman index. The FCI is structured as following:

$$FCI_i = 1-((\frac{\sum country_{i,1}}{nb\_inventor\_for_i})^2+(\frac{\sum country_{i,2}}{nb\_inventor\_for_i})^2+(\frac{\sum country_{i,3}}{nb\_inventor\_for_i})^2+\ldots) \quad (4.2)$$

Where FCI_i is the Forward Citation Concentration Index for patent family i. $country_{i,1}$, $country_{i,2}$ $country_{i,3}$ are the different residence countries where the inventors of forward citations reside. $nb\_inventor\_for_i$ is the total number of inventors of forward citations received by patent family i within five years after the publication date.[12] This indicator ranges from 0 to 1, with a smaller value indicating a greater degree of geographical concentration. The Forward Citation Index (FCI) quantifies the international spillover effect of an invention's knowledge. This index is calculated based on the geographic locations of inventors who cite the invention within five years of its publication. Essentially, the FCI measures how many different countries' inventors have referenced the invention to develop new technologies, indicating the extent of the invention's international knowledge dispersion. Specifically, an index value closer to 1 suggests that the invention's knowledge has been widely disseminated, as evidenced by the diversity of countries where the inventors of forward citations reside. Taking Figure 4.1 as an example and considering that the total number of inventors of forward citations is 6 (C1 has been removed

[12] To calculate the FCI_i, the denominator should be the total number of inventors of forward citation. The forward citation counts are still calculated within 5 years after publication date of each patent family member. This is because each forward citation may have more than 1 inventor and inventors may come from different countries, which means that a forward citation may correspond to more than one inventor's country of residence. However, there is a one-to-one correspondence between the inventor and the country of residence of the inventor. By using the total number of forward citations' inventors as the denominator, we ensure that the total number of inventors' countries equals the total number of inventors. Then FCI can be calculated.

as it is considered as self-citations and the inventor is from the US). The FCI for invention A is calculated as:

$$FCI_i = 1 - ((\frac{2}{6})^2 + (\frac{1}{6})^2 + (\frac{1}{6})^2 + (\frac{1}{6})^2 + (\frac{1}{6})^2) = 0.78 \tag{4.3}$$

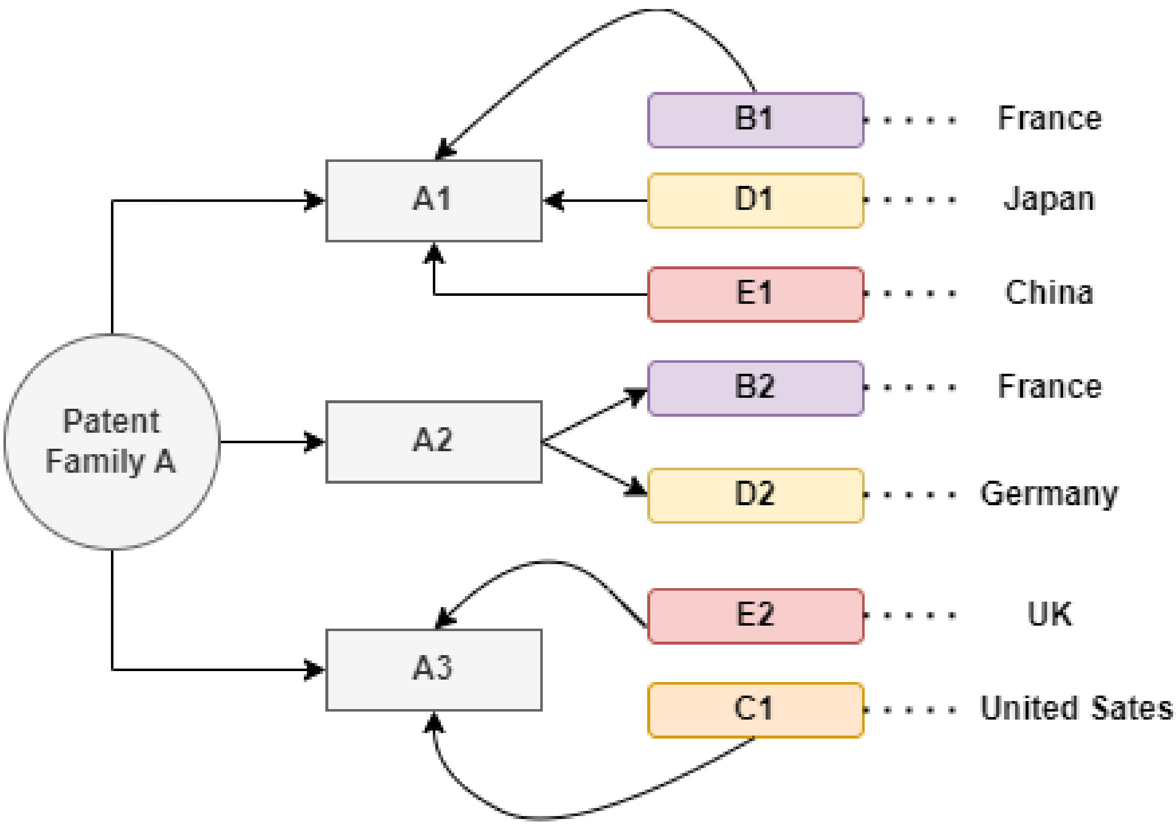


Figure 4.1: Forward citation links

Source: Own work.

Note: We have a simply patent family A which has three family members (A1, A2 and A3). B1 and B2 are two patent family members of patent family B. B1 is invented by an inventor who residents in France, and B2's inventor is also from France. D1 and D2 are patent family members of patent family D. D1's inventor is living in Japan and D2's inventor is living in Germany. Patent family E has two members (E1 and E2). E1's inventor is from China while E2's inventor is from the UK. Within five years after the publication, A1 is cited by B1, D1 and E1. A2 is cited by B2 and D2. A3 is cited by E2 and C1. Patent family A is cited by patent family B, C, D and E.

Explanatory variables and control variables

In order to explore the quality of different inventions and their international knowledge spillover effects, we divide inventions into eco and non-eco inventions and into international collaborative and non-collaborative inventions.[13] Our explanatory variables are 'eco' and 'co' which are two dummies that equal one if the invention is eco-innovation or an international collaborative innovation or zero otherwise . [14]

In addition to the core explanatory variables, we also control for the characteristics of invention from multiple dimensions. The backward citation refers to patents citing other patents (Squicciarini, Dernis, and C. Criscuolo, 2013). During the patent application and examination process, in order to determine the novelty and inventiveness of the patent, applicants and examiners need to conduct research on prior art. Therefore, in patent documents, it is usually necessary to cite previous documents related to its technical field to prove the difference between the invention and prior art (OECD, 2009). Backward citations, measured as the total number of prior simple patent families that is used as reference, reveal the prior art before the invention, which can help inventors and patent examiners identify the gap between the patented technology and the prior art, thereby determining the novelty and inventiveness of the invention (OECD, 2009). Backward citations can also help researchers understand the research results of different research teams and experts in the same field, thereby promoting technical exchanges and cooperation (OECD, 2009). Backward citations are also divided into patent and non-patent literature citations. Patent citations usually include citing previously authorised or applied patents, while non-patent literature citations refer to non-patent materials such as academic papers, technical reports, and books.

[13] According to the green IPC Inventory Scheme, if the invention has at least one green IPC code, the invention could be defined as 'eco'.

[14] Eco-innovations could also be international collaborative innovation.

Both types of citations are considered key factors when assessing the quality of a patent (Harhoff, Scherer, and Vopel, 2003). High-quality patents usually have more backward citations, because it means that inventors have a deep understanding of the existing technical field, which helps to improve the innovation (A. B. Jaffe and Trajtenberg, 2002). However, an excessive number of backward citations may also mean that the patent relies too much on previous inventions. In such cases, the patent may be somewhat unoriginal and rely too heavily on existing technology without significantly improving or innovating the technology (Lanjouw and Schankerman, 2001).

In addition to backward citations, this paper also uses 'patent scope' as a measure to control for the technological and economic value of an invention (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017). There is a relationship between the technological breadth of an invention and the potential economic value. The technological breadth of an invention can be understood as the extent of the technical field covered by an invention. The greater breadth means that the invention has practicability in more application fields, thereby increasing its potential economic value (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017). To be more specific, an invention that is broadly applicable to multiple technical fields may attract more potential investors, thereby increasing its market value. In addition, inventions with a wide range of application fields can generate knowledge spillovers in different industries and technical fields and promote more innovative activities (Marco, Sarnoff, and Charles, 2019). These inventions can provide researchers and enterprises in different fields with new ideas and technical foundations, thereby promoting the technological progress of the entire society (Marco, Sarnoff, and Charles, 2019). The 'patent scope' proposed by Joshua Lerner (1994) defines the 'scope' of a patent in terms of the total number of distinct IPC codes listed in the patent document. Our paper follows this idea and construct the 'scope' of a patent family to represent the technological breadth of an invention. The measurement is defined as:

$$Scope_A = n_A; n \in \{IPC_1; IPC_2; IPC_3; IPC_4 ....; IPC_n\} \tag{4.4}$$

Where $Scope_A$ is the scope value of an invention. n_A is the total number of distinct IPC codes listed in the patent documents. The larger the value, the greater technological breadth and market value of the innovation (Squicciarini, Dernis, and C. Criscuolo, 2013).

We also control for the time needed to grant an invention. Studies have shown that there is a relationship between patent examination time and patent quality (Harhoff and S. Wagner, 2009). One explanation is that applicants may devote more energy and resources to patents they consider more important in order to accelerate the review process (Régibeau and Rockett, 2010). For example, they may submit more detailed documentation, clearer technical descriptions, and rigorous claims to make it easier for examiners to understand and evaluate the validity and novelty of a patent (Squicciarini, Dernis, and C. Criscuolo, 2013). These practices can improve the quality of patents and potentially reduce examination time. For each invention, the '$time - span_A$' is:

$$time{-}span_A = \frac{(pub_1 - appln_1) + (pub_2 - appln_2) + (pub_3 - appln_3) + ... + (pub_k - appln_k)}{k} \tag{4.5}$$

Where k denotes the family size (the total number of patent family members of an invention). $pub_1 ... pub_k$ are the earliest publication date of each patent family member. $appln_1 ... appln_k$ are the application date of each patent family member. '$time - span_A$' is the average time needed to publish an invention.

Moreover, we calculate the total number of inventors and patent family size as control variables.[15] Having more R&D personnel means that enterprises or research institutions can invest more resources in technology R&D, which could lead to more innovation and higher quality inventions. At the same time, a larger patent family usually means that the inventor has higher confidence in his invention, which also attracts more forward citations. We also controlled for fixed effects. Specifically, we control for earliest application time fixed effects, earliest publication time fixed effect and categories of applicants for each invention.[16] At the same time we also control for the technical field of each invention, and previous research only control for the technological fixed effect and earliest application time fixed effects (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017). Besides, To control the differences in R&D capabilities between the US and other countries,we also include a dummy 'US' used to control for inventors' residence country. If the invention has the inventor living in the US, the dummy will be equal one. Otherwise it will be zero.

4.4 Exploratory data analysis

Our sample consists of 2,210,718 samples in total (Table 4.1).[17] There are 355,792 green innovations, which represents 16.09% of the total. Additionally, 182,535 international collaborative innovations were made, or 8.26% of the entire sample. By creating and implementing environmental protection technologies, lowering pollution, increasing resource utilisation efficiency, and lowering energy consumption, eco-innovation primarily achieves the protection

[15]Patent family size is defined as the total number of patent family members in one simply patent family. In our data, each patent family member should be granted between the year 2001 and 2017.

[16]The categories include company, hospital, government, university, non-profit organisation and individual.

[17]Our data is collected from PATSTAT database. We focus on patent families first granted at the USPTO between 2001 and 2017, and the earliest application year is between 2000 and 2016. Our paper focus on the inventions first published in USPTO because the United States not only leads annually in the number of patent applications but is also a very popular residence for inventors according to the our chapter 2. Since entering the 21st century, there has been rapid technological developing, leading us to focus on patents inventions after the year 2000.

and enhancement of the environment. This promotes a balance between economic development and environmental conservation, which benefits both human welfare and ecological sustainability on a global level (René Kemp and Pearson, 2007). Cooperation allows nations to share knowledge and adopt successful strategies, accelerating the creation, dissemination, and use of new technology (Dearing, 2009). Table 4.1 shows that international cooperative innovations or eco-inventions represent a sample proportion of innovation in our sample. The potential and influence of these two types of innovation, however, may be substantial in tackling global environmental issues and advancing sustainable development, which means that in the future, it may be necessary to increase R&D investment in stimulating international cooperation and eco-innovation.

Table 4.1: Share of eco-innovation and international technological collaboration in total sample

Invention	**Frequency**	**Share**
International non-collaborative innovation	2028183	91.74%
International collaborative innovation	182535	8.26%
Non-eco innovation	1854926	83.91%
Eco-innovation	355792	16.09%
Total inventions	2210718	100%

Source: Author's own calculations based on PATSTAT data.

Table 4.2 presents the distribution of patents across technology fields for inventions first published at the United States Patent Office (USPTO) between 2001 and 2017. During this period, physics-related inventions accounted for 44.89%, while electrical-related inventions accounted for 37.03%, and the number of these two categories of inventions far exceeded the number of inventions in the fields of transportation, human necessities, chemistry and medicine. A significant factor contributing to the unequal advancement of technology is the inclination towards specific investment directions (Greenwood, 1997). The physics domain encompasses inventions such as signalling, photography, high-performance computing, data storage, and nuclear energy, while the electrical field covers innovations like fibre optics, electronic communication devices, and semiconductors. The inventions within the realms of physics and electrical engineering tend to yield greater economic benefits, subsequently attracting increased investment. Furthermore, the growth of these fields is intimately linked to the demands of contemporary technology and industry (Qureshi, 2020). As electronic products, communication, and internet technologies become more widespread, the expansion requirements of these disciplines have surged, propelling a multitude of novel inventions (Mowery and Rosenberg, 1999). Simultaneously, in devising science and technology policies, governments might prioritise the progression of the physics and electrical sectors, furnishing additional policy backing and financial assistance for research in these areas (Hounshell, Rosenbloom, and Spencer, 1996).

The chemical industry encompasses a diverse array of technologies and processes, including cement production, explosives manufacturing, metallurgy, and many others. As this industry has substantial environmental implications, such as the production, utilisation, and disposal of chemicals, the growing awareness of environmental protection has prompted increased attention to eco-innovations in the chemical field (Sigman, Ladeuille, and Grandy, 2001). Among innovations in the field of chemistry, more than 26% of innovations are eco-based and about 13% of innovations are collaborative innovations. Therefore, various forms of cooperation are of great significance in these fields. For example, drug discovery is a complex and costly process that requires collaboration on a global scale. For example, the American pharmaceutical company

Pfizer and the German biotechnology company BioNTech have cooperated to develop a COVID-19 vaccine. This cooperation has accelerated the vaccine development process and helped the global fight against the epidemic (Bloom et al., 2021). Another example is hydrogen, a clean energy with broad application prospects and a significant level of international collaborations between countries such as Japan, Germany, and the United States have cooperated in the research of hydrogen energy. The International Clean Energy Agency (IEA) launched an international project called the 'Hydrogen Energy Technology Cooperation Program', which aims to promote the R&D, application and magnetisation of hydrogen energy. The program brings together governments, industries, and research institutions around the world to jointly carry out technology assessment, policy analysis, and market prospect research to provide strategic support for the development of hydrogen energy technology (Elam et al., 2003).

Table 4.2: Uneven distribution of innovation in each technology field

Technology fields	% of Total innovation	% of eco in each field	% of co in each field
HUMAN NECESSITIES	17.26%	13.49%	6.96%
TRANSPORTING	18.93%	15.07%	6.44%
CHEMISTRY; METALLURGY	8.98%	26.06%	13.72%
TEXTILES; PAPER	0.78%	8.44%	10.63%
FIXED CONSTRUCTIONS	3.25%	18.65%	6.09%
MECHANICAL ENGINEERING	9.37%	20.33%	5.71%
PHYSICS	44.89%	18.99%	8.80%
ELECTRICITY	37.03%	17.04%	10.02%

Source: Author's own calculations based on PATSTAT data.

Figure 4.2 shows the ranking of the countries where the inventors of eco-inventions live. First of all, during the period of our study, the United States occupies the first place, with about 63.88% of eco-inventions designed by inventors living in the United States. This is followed by Japan at around 14%, indicating that 14% of eco-inventions involve the effort of inventors living in Japan. The third is the Republic of Korea. The leading role of the United States, Japan and the Republic of Korea in eco-innovation can be attributed to several reasons. These countries possess strong R&D capabilities and strict environmental regulation, which creates a favourable environment for fostering eco-innovation (René Kemp and Pearson, 2007). In addition to the prominent roles played by the top three countries in eco-innovation, it is important to recognise that a considerable number of the top 50 inventor residences are in European countries. This observation underscores the significant contribution of European inventors to the development of green technologies. It is notable that among the top-ranking countries in green technology development, only China and India are considered developing countries. This highlights the progress these two emerging economies have made in the area of eco-innovation, despite the challenges associated with their rapid development, population growth, and resource constraints (Bao and C.-l. Fang, 2007; Coale and Hoover, 2015). Their commitment to environmental protection and sustainable development demonstrates their potential to become key players in the global transition towards a greener future (Xie, Yuan, and J.-j. Huang, 2017; Greenstone and Hanna, 2014).

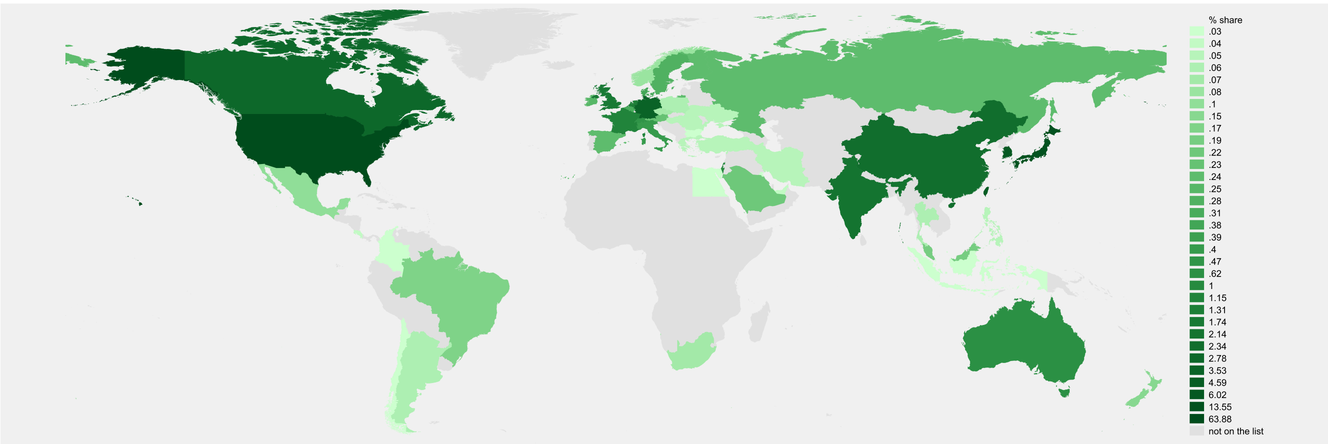


Figure 4.2: The distribution of inventors' country of residence for eco-innovation (top 50)

Source: Author's own calculations based on PATSTAT data.

Full ranking could be seen in Table C.2 in the Appendix.

Figure 4.3 shows the ranking of the countries where the inventors of international collaborative innovation live. It indicates that 79.91% of inventions were jointly developed by inventors living in the United States with inventors living in other countries, while 21% of the inventions were also jointly developed by countries other than the United States. This result is not surprising since we focused on international technological collaboration that was first published in the United States between 2001 and 2017. The second place is China, meaning that approximately 19% of international collaborative innovations involved technical input from Chinese inventors. The third is India, followed by Canada, Germany and the UK. The data does show that, in addition to the United States, the major players in international technological collaboration are still developed countries in Western Europe, such as Germany, Canada and the UK due to these countries having strong ability in R&D (René Kemp and Pearson, 2007). China and India remain the top-ranking developing countries, and thus among important invention partners for the United States. During the period of our study, both China and India attach great importance to innovation and international cooperation and have formulated various policies to promote cross-border cooperation and technological sharing. Specifically, these countries have signed many bilateral and multilateral cooperation agreements with countries such as the United States to strengthen cooperation in innovation (Pai, Tseng, and Liou, 2012), and their market potential makes them important partners for the United States in global innovation cooperation (Tiwari and Herstatt, 2012).

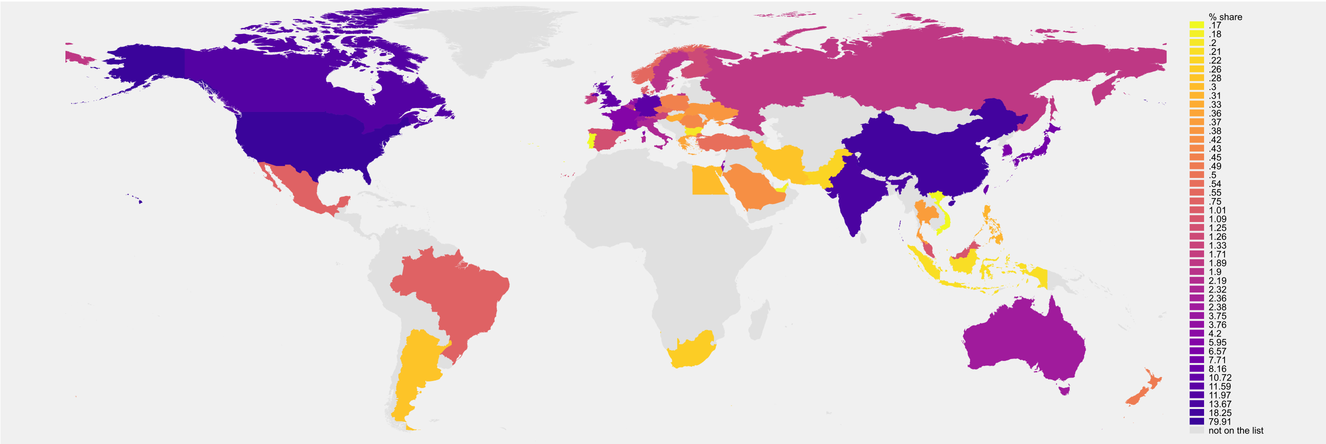


Figure 4.3: The distribution of inventors' country of residence for international collaborative innovation (top 50)

Source: Author's own calculations based on PATSTAT data.

Full ranking could be seen in Table C.3 in Appendix.

The data presented in Figure 4.4 highlights the global impact of eco-innovation first published in the United States between 2001 and 2017. By calculating the distribution of inventor residence countries of forward citations received by eco-innovation, we can gain a clearer understanding of how knowledge from eco-innovation has been disseminated across other countries. Within 5 years of an invention's publication, significant knowledge spillover from eco-innovation is observed in inventor countries such as Japan, Korea, and Germany. China, in particular, stands out with 5.46%, which means about 5.46% of forward citations have Chinese inventors. This demonstrates China's engagement with and adoption of knowledge originating from the United States eco-inventions. The diffusion of knowledge to other nations like Japan, the Republic of Korea and Germany further emphasises the global impact of the United States' eco-innovation during this period. Such spillover effects can stimulate eco-innovation, collaboration, and industrial upgrading in the receiving countries (Antoine Dechezleprêtre, Martin, and Mohnen, 2013).

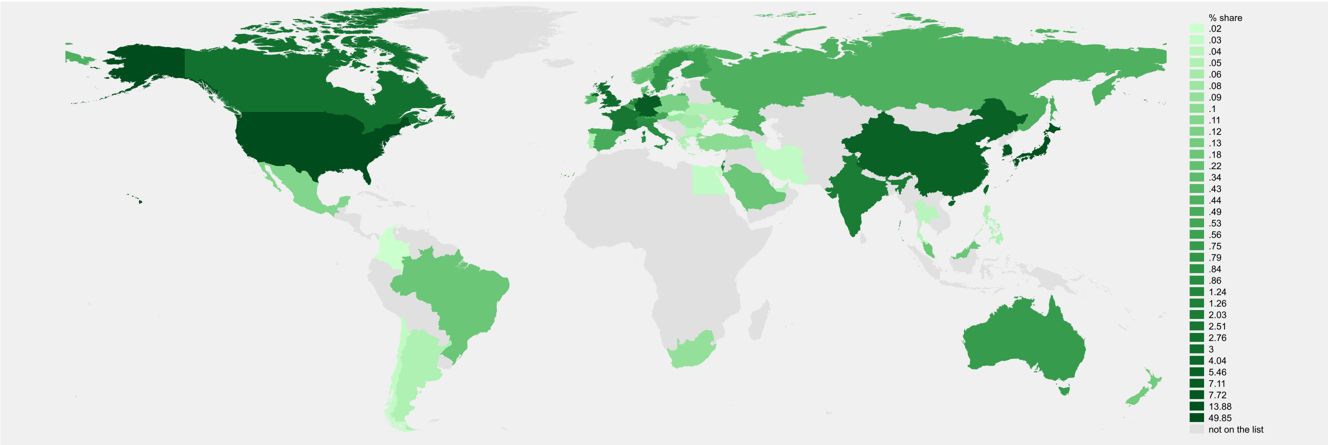


Figure 4.4: The distribution of inventor countries of forward citations (eco-innovation)

Source: Author's own calculations based on PATSTAT data.

Full ranking could be seen in Table C.4 in Appendix.

Figure 4.5 illustrates the knowledge spillover effects resulting from international collaborative innovation initially published in the United States between 2001 and 2017. It shows that 53% of forward citations associated with collaborative innovations initially published in the United States are attributed to inventors residing within the United States. In addition to the United States, Japan, the Republic of Korea, China and Germany play a significant role as both innovation partners and beneficiaries of technology spillovers from innovations published in the United States. By citing and adopting the technical knowledge embedded in inventions originating from the United States, these countries can integrate cutting-edge ideas and solutions into their own R&D processes. This, in turn, can lead to further innovations and drive economic growth.

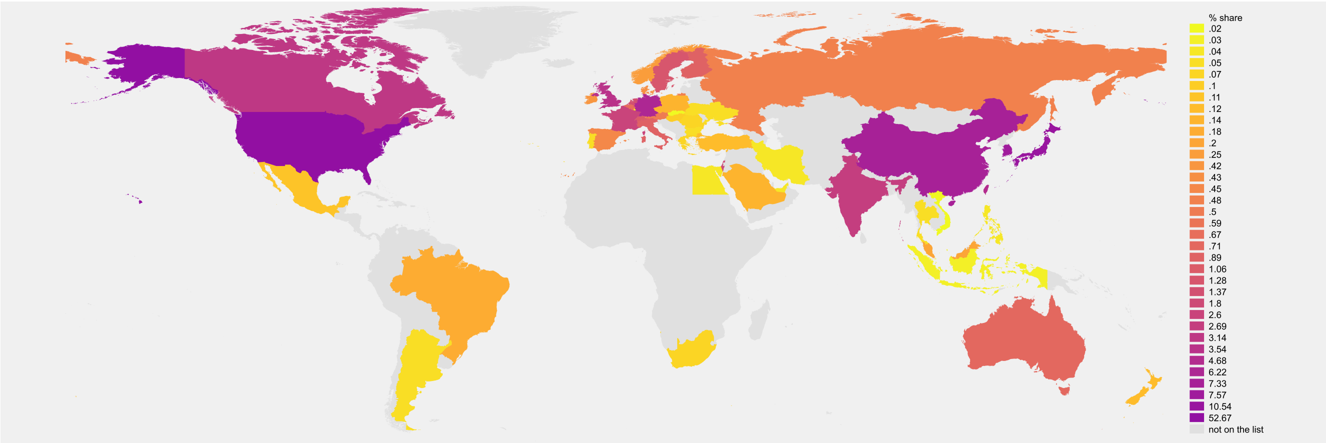


Figure 4.5: The distribution of inventor countries of forward citations (international collaborative innovation)

Source: Author's own calculations based on PATSTAT data.

Full ranking could be seen in Table C.5 in Appendix.

4.5 Econometric methodology

In order to conduct our research, we use data on patent families first granted at the USPTO between 2001 and 2017. We applied the PPML method. Poisson regression is now the standard method for modelling 'count data'. As with ordinary least squares, consistent estimates for Poisson regression require correct specification of the assumption of the conditional mean of the dependent variable (Gourieroux, Monfort, and Trognon, 1984). Under this condition, Poisson regression can be transformed into Poisson pseudo maximum likelihood (PPML) regression. Gourieroux, Monfort, and Trognon (1984) relax the assumption on the distribution of the dependent variable, which makes the PPML not restricted to the count data. Therefore, Poisson pseudo-maximum likelihood (PPML) regression can be applied to any non-negative dependent variable. PPML is often used to deal with the problem of zero value of the dependent variable. In fact, PPML seems to be the best choice when there are many zeros in the non-negative data

(Silva and Tenreyro, 2011). In our data, there are about 12% of zeros. And this is often the case in areas such as corporate R&D spending, patent citation counts, daily product sales, doctor visits, company credit, auction bidders, and inter-regional commuters. The PPML method has the ability to deal with zero-inflated data, overdispersed data and heteroscedasticity, which could mitigate the non-converge problem of traditional Poisson regression (Silva and Tenreyro, 2006). Moreover, whether dealing with underdispersed problems (conditional variance smaller than the conditional mean) or overdispersed problems (conditional variance larger than the conditional mean), PPML estimates remain consistent (Silva and Tenreyro, 2006). Following Van Zeebroeck and Van Pottelsberghe de la Potterie (2011) and Antoine Dechezleprêtre, Ménière, and Mohnen (2017), we estimate models of the general form:

$$D_i = f(X_i, C_i, F_i) \tag{4.6}$$

Where D_i is the measure of quality and international knowledge spillover effect of patent family i. X_i is main explanatory variables including 'Eco' and 'Co', which are two dummies to distinguish whether the innovation is eco or non-eco, international collaborative or non-collaborative respectively. C_i is a vector of other control variables which measure different characteristics of patent family i. F_i includes a set of fixed effects.

As we discussed in the previous section, We use two different measures to capture the quality and the international knowledge spillovers of the innovation:

- Forward citations received by the invention i within five years from the publication date. We exclude repeated citations and self-citations. The Forward citation is normalised according to the maximum value of forward citation of the invention in the same cohort;[18]

[18] If the inventions has the same technological field and the same earliest publication year, they could be considered

- Forward Citation concentration index (FCI), used to measure the international knowledge spillover effects. The FCI is normalised according to the maximum value of forward citation of the invention in the same cohort;

The following features of patent family i are included in the vector C_i:

- 'backward citations' is used to measure the patentability and novelty of innovation. The Backward citation is normalised according to the maximum value of backward citation of the invention in the same cohort;
- 'Scope' is used to control for the technological breadth of innovation. The 'scope' is normalised according to the maximum value of the 'scope' of the invention in the same cohort;
- 'Family Size' is normalised according to the maximum value of 'Family Size' of the invention in the same cohort;
- 'Time_span' controls for the importance of an invention and the potential market value;
- 'number of inventors' controls for the technical complexity of innovation. It is also normalised according to the maximum value;
- 'US' is a dummy used to control for inventors' residence country. If the invention has inventors living in the US, 'US' will be one. Otherwise, it will be zero.

F_i includes a set of fixed effects:

- Technological classification fixed effect;
- Applicants sector fixed effects;

as in the same cohort.

- Earliest application year fixed effects;
- Earliest publication year fixed effects.

4.6 Empirical findings

4.6.1 Base Model Results

The regression results in Table 4.3 show some interesting relationships between patent quality and international knowledge spillover effects. Regardless of the type of invention, columns one and two observe a positive relationship between backward citations, technological breadth, family size, the total number of inventors and patent quality (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017).[19] This implies that when an invention has more backward citations, a broader technological scope, a larger patent family, and more inventors involved, its guidance effect on future technologies becomes stronger. Innovations involving US inventors have a higher forward citation index than innovations without American inventors. Specifically, everything else being equal, for every 10% increase (0.1 units) in the backward citation index, the forward citation index (removing inventor self-citations or removing both inventor and applicant self-citations) of the invention increases by approximately 24% and 22% respectively.[20] Additionally, with every 10% increase in the invention's technological breadth, its quality increases by approximately 2.4% and 2.3% respectively. However, we found that the average time from application to publication of an invention is negatively correlated with the invention's quality. Specifically, the longer the examination time, the lower the quality of the invention.

[19] 'Inv' means the forward citation index or spillover effect is calculated based on the forward citation after removing inventor self-citations. 'Inv & app' means the forward citation index or spillover effect is calculated based on the forward citation after removing both the inventor and applicant self-citations.

[20] As backward citation may have zero values, the paper does not take a logarithm to avoid missing data problems.

Our results also show the backward citations, technological breadth, patent family size, the number of inventors and inventor country are all associated with the cross-border spillover effects of technology (Antoine Dechezleprêtre, Martin, and Mohnen, 2013). Specifically, we used the citation concentration index to measure the spillover effect of knowledge. Columns 3 and 4 show that, the broader the technological scope of the invention, the more backward citations, the greater the number of inventors, the larger the patent family, and the shorter the time required for review, the lower the concentration level of forward citation's inventor countries, which means the said invention tend to have their technological content disseminated more widely on a global scale. This is also reflected in inventors from various countries citing the said invention as a reference, which implies a stronger international knowledge spillover effect. Innovations involving US inventors also have stronger knowledge spillover effects than innovations without American inventors. For instance, everything else being equal, for every 10% increase in patent scope, the spillover effect increases by approximately 1%. Similarly, we still confirmed that the average time required for invention examination inversely affects the international spillover effect of technology. Consequently, the longer the review time for an invention, the less conducive it is to the global diffusion of knowledge across geographical locations.

Next, our results primarily demonstrate the impact of eco-innovation ('eco') and international collaborative innovation ('co') on the quality of inventions and the international spillover effect of knowledge. Overall, our results indicate that, after controlling for fixed effects such as the technological scope of the invention, and the earliest application and publication year, eco-innovation has a stronger guiding effect on future inventions and a more pronounced technology spillover effect compared to non-eco innovation (Antoine Dechezleprêtre, Martin, and Mohnen, 2013; Barbieri, Marzucchi, and Rizzo, 2020). Compared to non-collaborative innovation, global collaborative innovation also exhibits better quality and strong knowledge spillover effects. Specifically, the forward citation index for eco-innovation is approximately between 4.08% and 5.65% higher than that of non-eco innovation. The forward citation index for global collaborative innovation is approximately 2.94% higher than that of non-collaborative innovation. This demonstrates that both eco-innovation and collaborative innovation have a stronger technological guidance effect on future inventions.[21] In addition to the quality of inventions, our results also show that compared to non-eco innovation, eco-innovation has a stronger international knowledge spillover effect. This is reflected in more geographically dispersed forward citations' inventor residence countries for eco-innovation. Besides, collaborative innovation also has a stronger impact on knowledge spillover than non-collaborative innovation which means the collaborative innovation would be cited by inventors from a broader range of countries.

Furthermore, We conducted checks at the technological field level for the basic specifications. Table 4.4 presents the regression results for innovations related to human necessities. After narrowing the research scope to inventions related to human necessities, we find that compared to non-eco innovation, eco-innovation is cited less frequently. According to the World Intellectual Property Organisation (WIPO), inventions related to human necessities mainly involve the fields of food, clothing, furniture, etc. Generally, inventions related to this technology field are mainly used to meet basic living needs and improve the quality of life. According to our data, the proportion of eco-innovation related to human necessities is relatively low compared to other fields, accounting for only about 13%. This percentage can be interpreted from the perspective of the elasticity of essential goods (Andreyeva, Long, and Brownell, 2010). The elasticity of essential goods is usually low, which means that people's demand for these goods is relatively stable. Therefore, when buying essential goods, people may pay more attention

[21] $(e^{0.041} - 1) * 100\% = 4.08\%$; $(e^{0.055} - 1) * 100\% = 5.65\%$; $(e^{0.029} - 1) * 100\% = 2.94\%$

to factors such as price, quality, and convenience, while relatively overlooking environmental protection and sustainability. This may lead to lower market demand for eco-innovation, thus affecting the proportion of eco-innovation in these fields. Furthermore, firms' innovation in the field of essential goods may be more inclined towards non-eco innovation that is beneficial for reducing costs, improving productivity, and meeting consumer demands. Therefore, during the innovation process, they may prioritise citing the technical content of non-eco innovation. Similarly, we can also extend the conclusion to demonstrate that compared to non-collaborative innovation, collaborative innovation has lower quality in stimulating future innovation. Although both eco-innovation and collaborative innovation in this field have lower forward citation indexes, collaborative innovation still exhibit greater global knowledge spillover effects- that will be cited by inventors from a wider range of countries.

However, from Table 4.5 we cannot find evidence to prove that in the technical field of paper and textiles, eco-innovation and global collaborative innovation have any advantages in promoting technological progress. First, compared with other technical fields, the number of innovations in this field is relatively small, and the number of eco-innovations and global collaborative innovations in this technological field is relatively small.[22] The potential reasons for this result are closely linked to the characteristics of the technology sector in question. Specifically, in the paper and textile industries, production processes are more reliant on existing technologies, which are typically well-established and cost-effective, compared to early-stage technologies that might be untested and relatively expensive. The adoption of widely implemented technologies seems to meet the production needs of enterprises. Our data indicates that the annual introduction of new technologies in these sectors is comparatively lower than in other technological

[22]There are only about 1450 eco-innovation and 1000 collaborative innovation in this technology field and included in our data.

fields. Particularly in the textile industry, the advancement of production is largely dependent on skilled labour and the setting of styles, rather than on innovations in fabric that might drive industry progress, which constitute only a minor component. As a result, there might be a perception that the imperative for further eco-innovations and international collaborative innovations is diminished. Nevertheless, it is noteworthy that collaborative innovation continues to yield pronounced effects in terms of facilitating knowledge spillovers. This phenomenon can be attributed to the fact that even within this technology field, international collaborative inventions entail the merge of insights from diverse countries, thereby increasing the likelihood of broader citation across inventors from multiple countries.

Table 4.6 illustrates the quality and knowledge spillover effects within the technological field of fixed construction. When compared to non-eco innovation and non-collaborative innovation, the results still show that both eco-innovation and collaborative innovation demonstrate superior quality and stronger knowledge spillover effects. Table 4.7 presents the regression results for inventions related to transportation and performing operations. According to WIPO, this field includes inventions related to transportation vehicles, printing, and large-scale production machinery. In this field, eco-innovation and global collaborative innovation provide stronger technical guidance for future inventions. First, the transportation sector is closely related to environmental issues, especially air pollution and greenhouse gas emissions. Therefore, in these high-pollution fields, eco-innovation may receive greater attention and policy support, thereby providing stronger technical guidance for future inventions (Arundel and René Kemp, 2009). Moreover, eco-innovation and global collaborative innovation typically involve more R&D input and inventors, which means they encompass more technical content and may have good knowledge spillover effects. This characteristic is also applicable to inventions in other high-tech fields, such as chemistry, electrical, and mechanical engineering. Inventions pertaining to transportation and large-scale industrial machinery are often intricately tied to economic profits. For instance, a nation's manufacturing sector relies heavily on production machinery, and the economic advancement of a country is closely intertwined with efficient transportation systems (Gutowski et al., 2013; F. Yang and S. Gu, 2021). The environmental challenges can be mitigated through the application of green technologies in this technology field. As previously discussed, inventions borne out of international collaborations tend to exhibit a high technological content. Hence, both eco-innovation and collaborative innovation in this technological field could furnish guidance for inventors from a multitude of countries.

Table 4.8 and Table 4.9 present the results in the technological fields of mechanical engineering and electricity. Our results show that in both technological fields, compared with non-eco innovation and non-collaborative innovation, eco-innovation and collaborative innovation have better quality and knowledge spillover effects. There are many inventions in the field of electricity, including many important breakthroughs from early batteries and motors to modern smart grids. This also includes many eco-inventions such as solar cells and wind turbines. In order to achieve safe and sustainable nuclear fusion energy, many countries have jointly established ITER (International Thermonuclear Experimental Reactor), which is a large-scale international cooperation project. Mechanical engineering represents a highly expansive and diverse domain, encompassing not just commodities and infrastructural components such as lighting and engines, but also extending into specialised and sensitive sectors like weapons. This gives rise to an array of specialised and complicated technological requirements. For instance, innovations in the realm of energy efficiency are more likely to gain societal and market traction, given their direct implications for energy efficiency and environmental sustainability (Boffo and Patalano, 2020).

This heightened societal and environmental impact further induces subsequent research. In sectors involving engines and other large-scale projects, the intricate technological requirements and associated high costs have caused an increasing trend toward international collaborative innovation, which means countries and companies are more inclined to engage in knowledge sharing (Lasi et al., 2014). Collaboration not only expedites the pace of R&D but also induces broader knowledge spillovers.

Table 4.10 presents results in the chemistry and metallurgy technological field. Our results show that eco-inventions have a higher forward citation index and stronger knowledge spillovers than non-eco inventions, and the knowledge spillover effect of collaborative innovation is also stronger than non-collaborative innovation. Chemistry and metallurgy often involve complex chemical reactions and handling of substances that can produce harmful substances. This field is also involved in the development of new materials, and green materials or recyclable materials will have higher forward citations (Lasi et al., 2014). Beyond this, metallurgical research often requires expensive equipment and specialised techniques. International collaboration can bring together more resources so knowledge spillovers are stronger. However, after excluding applicants' self-citations, we cannot prove that global collaborative innovation has more forward citations. The exclusion of applicant self-citation provides a more stringent evaluation standard because it requires that an invention is not only cited but also cited by an independent party unrelated to the original applicant. However, in chemical research such as medicine, applicants with a large number of inventions are often key figures or major research institutions in the field, and their inventions may often be the result of more collaboration with each other and be cited more by experts in the same field, which may be the underlying reason.

Table 4.11 presents the results in the physics technological field. Similarly, our results show that compared with non-eco innovation and non-collaborative innovation, eco-innovation has a larger forward citation index, and collaborative innovation has better knowledge spillover effects. However, it is worth noting that eco-inventions related to the field of physics have worse knowledge spillover effects than non-eco inventions. In the field of physics, eco-innovations (such as solar cells, wind turbines, energy-efficient materials, etc.) and non-eco innovations (such as general-purpose semiconductors, particle accelerators, quantum computing, etc.) have their own characteristics. Compared to non-eco innovations (such as semiconductor technologies), some eco-innovations (such as solar cells) may not yet be ready for commercialisation or mass production, which will affect its knowledge spillover in a wide range of applications. Besides, these technologies may be more specific and specialised, and may not be easily cited by other innovations (Cantwell and Janne, 1999). However, non-eco innovations such as semiconductors and superconductors usually have wider application scenarios and basic research value, thus promoting cross-field knowledge spillovers.

Table 4.3: TOTAL INNOVATION

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.041***	0.055***	0.019***	0.022***
					(0.003)	(0.003)	(0.002)	(0.002)
Co					0.029***	0.029***	0.088***	0.075***
					(0.004)	(0.004)	(0.002)	(0.002)
backward_citation	2.333***	2.189***	0.888***	0.879***	2.335***	2.191***	0.895***	0.884***
	(0.012)	(0.012)	(0.006)	(0.006)	(0.012)	(0.012)	(0.006)	(0.006)
log_timespan	-0.130***	-0.132***	-0.031***	-0.036***	-0.129***	-0.131***	-0.031***	-0.036***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log_patent_scope	0.230***	0.233***	0.094***	0.096***	0.228***	0.230***	0.093***	0.094***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log_number_of_patents	0.093***	0.095***	0.023***	0.025***	0.093***	0.095***	0.023***	0.025***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
log_number_of_inventors	0.119***	0.116***	0.044***	0.043***	0.116***	0.113***	0.035***	0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
US	0.360***	0.365***	0.200***	0.187***	0.356***	0.360***	0.190***	0.178***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	-1.195***	-1.219***	-0.344***	-0.304***	-1.226***	-1.257***	-0.387***	-0.344***
	(0.014)	(0.014)	(0.009)	(0.009)	(0.014)	(0.014)	(0.009)	(0.009)
Observations	2,210,690	2,210,690	1,593,635	1,567,569	2,210,690	2,210,690	1,593,635	1,567,569
Pseudo R2	0.045	0.043	0.017	0.016	0.045	0.043	0.017	0.016
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

Table 4.4: HUMAN NECESSITIES

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					-0.269***	-0.311***	-0.050***	-0.042***
					(0.009)	(0.009)	(0.006)	(0.006)
Co					-0.069***	-0.058***	0.069***	0.059***
					(0.010)	(0.010)	(0.006)	(0.006)
backward_citation	2.398***	2.284***	0.916***	0.889***	2.382***	2.267***	0.919***	0.891***
	(0.026)	(0.026)	(0.014)	(0.015)	(0.026)	(0.026)	(0.014)	(0.015)
log_timespan	-0.146***	-0.156***	-0.045***	-0.047***	-0.136***	-0.145***	-0.045***	-0.047***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
log_patent_scope	0.249***	0.252***	0.122***	0.123***	0.255***	0.258***	0.123***	0.124***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
log_number_of_patents	0.186***	0.192***	0.050***	0.048***	0.186***	0.193***	0.051***	0.049***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
log_number_of_inventors	0.091***	0.096***	0.044***	0.044***	0.089***	0.092***	0.037***	0.038***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
US	0.304***	0.296***	0.081***	0.075***	0.301***	0.292***	0.079***	0.073***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Constant	-0.879***	-0.793***	-0.118***	-0.112***	-0.885***	-0.804***	-0.139***	-0.128***
	(0.037)	(0.037)	(0.026)	(0.027)	(0.038)	(0.037)	(0.026)	(0.027)
Observations	381,519	381,519	228,438	225,021	381,519	381,519	228,438	225,021
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

Table 4.5: TEXTILES; PAPER

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.056	0.053	-0.000	-0.001
					(0.035)	(0.036)	(0.026)	(0.027)
Co					0.028	0.008	0.122***	0.108***
					(0.030)	(0.031)	(0.021)	(0.022)
backward_citation	1.459***	1.369***	0.614***	0.600***	1.460***	1.369***	0.621***	0.606***
	(0.061)	(0.061)	(0.041)	(0.043)	(0.061)	(0.061)	(0.041)	(0.043)
log_timespan	-0.055**	-0.040*	-0.027	-0.036**	-0.054**	-0.039*	-0.027	-0.037**
	(0.022)	(0.022)	(0.018)	(0.018)	(0.022)	(0.022)	(0.018)	(0.018)
log_patent_scope	0.342***	0.328***	0.136***	0.139***	0.339***	0.325***	0.136***	0.139***
	(0.020)	(0.020)	(0.016)	(0.017)	(0.020)	(0.020)	(0.016)	(0.017)
log_number_of_patents	0.091***	0.082***	0.055***	0.055***	0.092***	0.082***	0.058***	0.057***
	(0.021)	(0.021)	(0.017)	(0.017)	(0.021)	(0.021)	(0.017)	(0.017)
log_number_of_inventors	0.128***	0.122***	0.039***	0.037***	0.125***	0.121***	0.026**	0.026**
	(0.016)	(0.016)	(0.012)	(0.013)	(0.016)	(0.016)	(0.013)	(0.013)
US	0.055**	0.086***	0.105***	0.078***	0.052**	0.084***	0.092***	0.066***
	(0.024)	(0.024)	(0.019)	(0.020)	(0.024)	(0.025)	(0.019)	(0.020)
Constant	-1.380***	-1.382***	-0.400***	-0.333***	-1.407***	-1.403***	-0.437***	-0.364***
	(0.152)	(0.152)	(0.124)	(0.127)	(0.153)	(0.152)	(0.124)	(0.127)
Observations	17,146	17,146	11,409	11,188	17,146	17,146	11,409	11,188
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

Table 4.6: FIXED CONSTRUCTIONS

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.068***	0.094***	0.049***	0.059***
					(0.012)	(0.012)	(0.010)	(0.011)
Co					0.059***	0.044**	0.110***	0.089***
					(0.019)	(0.019)	(0.014)	(0.014)
backward_citation	2.052***	1.969***	0.875***	0.876***	2.047***	1.964***	0.873***	0.873***
	(0.050)	(0.050)	(0.032)	(0.032)	(0.050)	(0.050)	(0.032)	(0.032)
log_timespan	-0.093***	-0.096***	-0.037***	-0.040***	-0.092***	-0.094***	-0.037***	-0.039***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
log_patent_scope	0.302***	0.300***	0.163***	0.164***	0.291***	0.286***	0.156***	0.155***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
log_number_of_patents	0.151***	0.150***	0.035***	0.039***	0.152***	0.151***	0.039***	0.042***
	(0.011)	(0.011)	(0.009)	(0.009)	(0.011)	(0.011)	(0.009)	(0.009)
log_number_of_inventors	0.060***	0.048***	0.044***	0.038***	0.055***	0.046***	0.033***	0.031***
	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
US	0.083***	0.079***	-0.044***	-0.053***	0.079***	0.075***	-0.049***	-0.058***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.012)	(0.012)	(0.010)	(0.010)
Constant	-1.376***	-1.416***	-0.187***	-0.184***	-1.432***	-1.481***	-0.246***	-0.241***
	(0.063)	(0.064)	(0.055)	(0.056)	(0.063)	(0.064)	(0.056)	(0.057)
Observations	71,742	71,742	45,904	45,392	71,742	71,742	45,904	45,392
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: (1)‘Inv’ means inventor self-citations have been removed. (2)‘Inv & app’ means both inventor self-citations and applicant self-citations have been removed.

Table 4.7: PERFORMING OPERATIONS; TRANSPORTING

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.239***	0.265***	0.154***	0.154***
					(0.006)	(0.006)	(0.004)	(0.004)
Co					0.015*	0.018**	0.091***	0.077***
					(0.009)	(0.009)	(0.006)	(0.006)
backward_citation	2.169***	2.054***	0.945***	0.938***	2.173***	2.058***	0.947***	0.941***
	(0.025)	(0.025)	(0.016)	(0.016)	(0.025)	(0.025)	(0.016)	(0.016)
log_timespan	-0.113***	-0.107***	-0.043***	-0.046***	-0.112***	-0.106***	-0.043***	-0.046***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
log_patent_scope	0.306***	0.311***	0.134***	0.136***	0.281***	0.283***	0.118***	0.121***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
log_number_of_patents	0.155***	0.153***	0.055***	0.054***	0.158***	0.157***	0.058***	0.056***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
log_number_of_inventors	0.067***	0.063***	0.040***	0.039***	0.064***	0.060***	0.031***	0.032***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
US	0.215***	0.236***	0.205***	0.186***	0.204***	0.223***	0.191***	0.173***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	-1.299***	-1.393***	-0.267***	-0.238***	-1.412***	-1.519***	-0.356***	-0.325***
	(0.033)	(0.034)	(0.025)	(0.026)	(0.033)	(0.034)	(0.025)	(0.026)
Observations	418,414	418,414	291,065	285,578	418,414	418,414	291,065	285,578
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

Table 4.8: MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.207***	0.220***	0.147***	0.149***
					(0.007)	(0.007)	(0.005)	(0.005)
Co					0.051***	0.051***	0.086***	0.070***
					(0.012)	(0.013)	(0.008)	(0.008)
backward_citation	2.228***	2.156***	0.972***	0.971***	2.217***	2.144***	0.960***	0.959***
	(0.039)	(0.039)	(0.022)	(0.023)	(0.038)	(0.038)	(0.022)	(0.022)
log_timespan	-0.094***	-0.090***	-0.032***	-0.034***	-0.094***	-0.090***	-0.032***	-0.035***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
log_patent_scope	0.341***	0.334***	0.148***	0.148***	0.309***	0.300***	0.126***	0.126***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
log_number_of_patents	0.109***	0.111***	0.033***	0.035***	0.115***	0.118***	0.039***	0.040***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)
log_number_of_inventors	0.065***	0.056***	0.024***	0.022***	0.059***	0.049***	0.015***	0.015***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.004)
US	0.181***	0.181***	0.078***	0.069***	0.171***	0.171***	0.067***	0.059***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Constant	-1.476***	-1.587***	-0.337***	-0.323***	-1.602***	-1.720***	-0.433***	-0.418***
	(0.042)	(0.043)	(0.032)	(0.032)	(0.042)	(0.043)	(0.032)	(0.032)
Observations	207,092	207,092	146,757	144,808	207,092	207,092	146,757	144,808
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (1)‘Inv’ means inventor self-citations have been removed. (2)‘Inv & app’ means both inventor self-citations and applicant self-citations have been removed.

Table 4.9: ELECTRICITY

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.060***	0.076***	0.024***	0.024***
					(0.004)	(0.004)	(0.002)	(0.002)
Co					0.038***	0.037***	0.079***	0.067***
					(0.005)	(0.005)	(0.003)	(0.003)
backward_citation	2.020***	1.868***	0.724***	0.724***	2.021***	1.868***	0.732***	0.730***
	(0.018)	(0.018)	(0.009)	(0.009)	(0.018)	(0.018)	(0.009)	(0.009)
log_timespan	-0.155***	-0.157***	-0.049***	-0.054***	-0.154***	-0.155***	-0.050***	-0.054***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
log_patent_scope	0.281***	0.283***	0.097***	0.100***	0.276***	0.276***	0.095***	0.098***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
log_number_of_patents	0.146***	0.147***	0.036***	0.038***	0.145***	0.147***	0.033***	0.036***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
log_number_of_inventors	0.092***	0.091***	0.039***	0.038***	0.087***	0.086***	0.031***	0.031***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
US	0.431***	0.437***	0.234***	0.222***	0.424***	0.431***	0.222***	0.212***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
Constant	-0.769***	-0.799***	-0.140***	-0.098***	-0.825***	-0.865***	-0.190***	-0.143***
	(0.024)	(0.024)	(0.013)	(0.013)	(0.024)	(0.025)	(0.013)	(0.013)
Observations	818,550	818,550	660,556	651,241	818,550	818,550	660,556	651,241
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

Table 4.10: CHEMISTRY; METALLURGY

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.043***	0.045***	0.072***	0.082***
					(0.008)	(0.008)	(0.006)	(0.006)
Co					0.019*	-0.004	0.092***	0.076***
					(0.011)	(0.010)	(0.007)	(0.007)
backward_citation	2.265***	2.112***	0.931***	0.913***	2.264***	2.111***	0.934***	0.915***
	(0.032)	(0.032)	(0.020)	(0.021)	(0.032)	(0.032)	(0.021)	(0.021)
log_timespan	-0.132***	-0.156***	-0.053***	-0.056***	-0.133***	-0.157***	-0.055***	-0.057***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
log_patent_scope	0.267***	0.276***	0.119***	0.123***	0.264***	0.273***	0.113***	0.116***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
log_number_of_patents	0.166***	0.176***	0.066***	0.061***	0.166***	0.176***	0.067***	0.061***
	(0.007)	(0.008)	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.005)
log_number_of_inventors	0.075***	0.093***	0.034***	0.032***	0.074***	0.095***	0.024***	0.024***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
US	0.205***	0.201***	0.166***	0.155***	0.201***	0.200***	0.150***	0.142***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
Constant	-1.160***	-0.923***	-0.209***	-0.201***	-1.176***	-0.930***	-0.273***	-0.267***
	(0.055)	(0.055)	(0.040)	(0.041)	(0.055)	(0.055)	(0.041)	(0.041)
Observations	198,502	198,502	125,574	122,364	198,502	198,502	125,574	122,364
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

Table 4.11: PHYSICS

	1	2	3	4	5	6	7	8
VARIABLES	**Forward Citations**		**Spillovers**		**Forward Citations**		**Spillovers**	
	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app	Inv	Inv & app
Eco					0.031***	0.051***	-0.007***	-0.006***
					(0.004)	(0.004)	(0.002)	(0.002)
Co					0.007	0.009*	0.071***	0.059***
					(0.005)	(0.005)	(0.003)	(0.003)
backward_citation	2.158***	2.000***	0.798***	0.792***	2.160***	2.003***	0.803***	0.796***
	(0.017)	(0.018)	(0.009)	(0.009)	(0.017)	(0.018)	(0.009)	(0.009)
log_timespan	-0.139***	-0.144***	-0.033***	-0.038***	-0.138***	-0.142***	-0.034***	-0.039***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
log_patent_scope	0.264***	0.266***	0.104***	0.106***	0.261***	0.262***	0.105***	0.107***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
log_number_of_patents	0.144***	0.150***	0.028***	0.033***	0.144***	0.150***	0.028***	0.032***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
log_number_of_inventors	0.085***	0.082***	0.035***	0.033***	0.084***	0.080***	0.028***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
US	0.456***	0.466***	0.265***	0.249***	0.453***	0.461***	0.257***	0.243***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	-0.836***	-0.843***	-0.287***	-0.232***	-0.861***	-0.883***	-0.309***	-0.250***
	(0.021)	(0.022)	(0.012)	(0.012)	(0.022)	(0.022)	(0.012)	(0.012)
Observations	992,339	992,339	769,168	755,132	992,339	992,339	769,168	755,132
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: (1)'Inv' means inventor self-citations have been removed. (2)'Inv & app' means both inventor self-citations and applicant self-citations have been removed.

4.6.2 Robustness Check

We have conducted a robustness analysis based on removing examiner citations when measuring forward citations and the knowledge spillover effects. ‘Examiner citations’ refer to the references cited by the patent examiner during the patent examination process. These citations are used to assess the novelty, non-obviousness, and usefulness of the patent application in question (P. Criscuolo and Verspagen, 2008). Although studies have shown that examiner citations play an important role in identifying prior art, the process of knowledge transfer between inventors cannot be accurately measured because such citations are not submitted by the inventor (P. Criscuolo and Verspagen, 2008). In this examination, we still evaluate various aspects, including factors such as the novelty, inventiveness, scope and inventor counts of the patent families, to assess the quality and international spillover effects of innovation. We still find that backward citations, family size, patent scope, and number of inventors are positively associated with the patent quality and knowledge spillover effects.

Our results still demonstrate that, in general, eco-innovation and global collaborative innovation are more conducive to promoting technological development and providing technical guidance for future inventions compared to non-eco innovation and non-collaborative innovation. Specifically, compared to non-eco innovations, eco-innovations exhibit a higher forward citation index, indicating a superior patent quality. Moreover, eco-innovations also demonstrate stronger technological spillover effects, although the magnitude of this effect varies across different technological fields. Compared with non-collaborative innovation, collaborative innovation shows a stronger technology spillover effect. It is worth noting that after deleting examiner citations, we have no evidence showing that collaboration in the field of transportation and physics has a larger forward citation index than non-collaborative innovation. According to Alcácer, Gittelman, and Sampat (2009), a higher proportion of patent examiners in communications and computer-related fields may imply that patent applications in these fields are more complex and more difficult to review. Especially within this technological field, global collaborative innovation tends to be of a more advanced and specialised nature. Innovations characterised as advanced and specialised typically find applicability within exceedingly specific applications or contexts. Consequently, these patents may not experience widespread citation unless subsequent research or inventions also transpire within the same or closely related professional domain.

Table 4.12: TOTAL INNOVATION (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.052***	0.023***
			(0.003)	(0.002)
Co			0.027***	0.079***
			(0.004)	(0.002)
backward_citation	2.378***	0.921***	2.380***	0.927***
	(0.013)	(0.007)	(0.013)	(0.007)
log_timespan	-0.129***	-0.032***	-0.128***	-0.032***
	(0.002)	(0.001)	(0.002)	(0.001)
log_patent_scope	0.206***	0.091***	0.203***	0.089***
	(0.002)	(0.001)	(0.002)	(0.001)
log_number_of_patents	0.066***	0.024***	0.066***	0.024***
	(0.002)	(0.001)	(0.002)	(0.001)
log_number_of_inventors	0.110***	0.046***	0.107***	0.038***
	(0.002)	(0.001)	(0.002)	(0.001)
US	0.462***	0.200***	0.457***	0.190***
	(0.003)	(0.002)	(0.003)	(0.002)
Constant	-1.640***	-0.422***	-1.677***	-0.466***
	(0.016)	(0.010)	(0.016)	(0.010)
Pseudo R2	0.057	0.023	0.057	0.023
Observations	2,210,686	1,401,639	2,210,686	1,401,639
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.13: HUMAN NECESSITIES (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			-0.341***	-0.032***
			(0.011)	(0.007)
Co			-0.070***	0.062***
			(0.011)	(0.007)
backward_citation	2.494***	0.956***	2.475***	0.958***
	(0.028)	(0.016)	(0.028)	(0.017)
log_timespan	-0.167***	-0.046***	-0.155***	-0.046***
	(0.006)	(0.004)	(0.006)	(0.004)
log_patent_scope	0.224***	0.112***	0.232***	0.113***
	(0.005)	(0.004)	(0.005)	(0.004)
log_number_of_patents	0.169***	0.051***	0.170***	0.053***
	(0.007)	(0.004)	(0.007)	(0.004)
log_number_of_inventors	0.105***	0.048***	0.102***	0.041***
	(0.005)	(0.003)	(0.005)	(0.003)
US	0.387***	0.085***	0.383***	0.083***
	(0.007)	(0.005)	(0.007)	(0.005)
Constant	-1.062***	-0.203***	-1.067***	-0.222***
	(0.042)	(0.031)	(0.043)	(0.031)
Observations	381,519	198,066	381,519	198,066
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.14: TEXTILES; PAPER (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.078*	-0.002
			(0.042)	(0.031)
Co			-0.007	0.100***
			(0.036)	(0.026)
backward_citation	1.519***	0.663***	1.517***	0.669***
	(0.065)	(0.048)	(0.065)	(0.048)
log_timespan	-0.068***	-0.031	-0.066***	-0.032
	(0.025)	(0.021)	(0.025)	(0.021)
log_patent_scope	0.274***	0.125***	0.269***	0.124***
	(0.023)	(0.019)	(0.023)	(0.019)
log_number_of_patents	0.029	0.055***	0.030	0.057***
	(0.024)	(0.020)	(0.024)	(0.020)
log_number_of_inventors	0.136***	0.034**	0.136***	0.024
	(0.019)	(0.015)	(0.019)	(0.015)
US	0.251***	0.103***	0.250***	0.092***
	(0.029)	(0.023)	(0.029)	(0.023)
Constant	-1.686***	-0.504***	-1.711***	-0.535***
	(0.176)	(0.147)	(0.177)	(0.148)
Observations	17,146	9,919	17,146	9,919
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.15: FIXED CONSTRUCTIONS (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.109***	0.069***
			(0.015)	(0.013)
Co			0.067***	0.103***
			(0.022)	(0.017)
backward_citation	2.142***	0.901***	2.136***	0.897***
	(0.054)	(0.038)	(0.054)	(0.038)
log_timespan	-0.096***	-0.036***	-0.094***	-0.035***
	(0.011)	(0.010)	(0.011)	(0.010)
log_patent_scope	0.262***	0.139***	0.246***	0.129***
	(0.011)	(0.010)	(0.011)	(0.011)
log_number_of_patents	0.114***	0.042***	0.116***	0.045***
	(0.013)	(0.011)	(0.013)	(0.011)
log_number_of_inventors	0.063***	0.054***	0.059***	0.045***
	(0.009)	(0.008)	(0.010)	(0.008)
US	0.174***	-0.058***	0.168***	-0.064***
	(0.014)	(0.012)	(0.014)	(0.012)
Constant	-1.744***	-0.288***	-1.824***	-0.355***
	(0.076)	(0.069)	(0.076)	(0.070)
Observations	71,740	38,044	71,740	38,044
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.16: PERFORMING OPERATIONS; TRANSPORTING (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.263***	0.160***
			(0.007)	(0.005)
Co			0.016	0.082***
			(0.010)	(0.007)
backward_citation	2.268***	1.000***	2.272***	1.003***
	(0.027)	(0.018)	(0.027)	(0.018)
log_timespan	-0.117***	-0.043***	-0.115***	-0.043***
	(0.006)	(0.004)	(0.005)	(0.004)
log_patent_scope	0.268***	0.129***	0.241***	0.112***
	(0.005)	(0.004)	(0.005)	(0.004)
log_number_of_patents	0.103***	0.047***	0.106***	0.050***
	(0.006)	(0.004)	(0.006)	(0.004)
log_number_of_inventors	0.067***	0.044***	0.064***	0.036***
	(0.004)	(0.003)	(0.004)	(0.003)
US	0.364***	0.202***	0.351***	0.188***
	(0.006)	(0.005)	(0.006)	(0.005)
Constant	-1.888***	-0.391***	-2.013***	-0.483***
	(0.039)	(0.030)	(0.039)	(0.030)
Observations	418,412	249,467	418,412	249,467
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.17: MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.270***	0.175***
			(0.008)	(0.006)
Co			0.057***	0.072***
			(0.015)	(0.010)
backward_citation	2.423***	1.046***	2.413***	1.037***
	(0.043)	(0.027)	(0.043)	(0.026)
log_timespan	-0.083***	-0.022***	-0.083***	-0.022***
	(0.007)	(0.006)	(0.007)	(0.006)
log_patent_scope	0.305***	0.141***	0.263***	0.114***
	(0.007)	(0.005)	(0.007)	(0.005)
log_number_of_patents	0.050***	0.023***	0.058***	0.030***
	(0.008)	(0.006)	(0.008)	(0.006)
log_number_of_inventors	0.058***	0.029***	0.051***	0.022***
	(0.006)	(0.004)	(0.006)	(0.004)
US	0.279***	0.077***	0.265***	0.064***
	(0.008)	(0.006)	(0.008)	(0.006)
Constant	-2.146***	-0.533***	-2.314***	-0.646***
	(0.050)	(0.039)	(0.050)	(0.039)
Observations	207,090	124,847	207,090	124,847
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.18: ELECTRICITY (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.068***	0.028***
			(0.005)	(0.003)
Co			0.038***	0.072***
			(0.006)	(0.003)
backward_citation	2.040***	0.761***	2.040***	0.768***
	(0.020)	(0.010)	(0.020)	(0.010)
log_timespan	-0.148***	-0.048***	-0.146***	-0.048***
	(0.004)	(0.002)	(0.004)	(0.002)
log_patent_scope	0.273***	0.101***	0.267***	0.098***
	(0.003)	(0.002)	(0.004)	(0.002)
log_number_of_patents	0.093***	0.037***	0.092***	0.034***
	(0.004)	(0.002)	(0.004)	(0.002)
log_number_of_inventors	0.088***	0.040***	0.083***	0.032***
	(0.003)	(0.002)	(0.003)	(0.002)
US	0.533***	0.235***	0.527***	0.224***
	(0.004)	(0.002)	(0.004)	(0.002)
Constant	-1.257***	-0.210***	-1.319***	-0.260***
	(0.028)	(0.015)	(0.028)	(0.015)
Observations	818,548	591,225	818,548	591,225
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.19: CHEMISTRY; METALLURGY (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.037***	0.100***
			(0.010)	(0.007)
Co			-0.002	0.076***
			(0.012)	(0.008)
backward_citation	2.357***	1.010***	2.356***	1.011***
	(0.035)	(0.023)	(0.035)	(0.023)
log_timespan	-0.183***	-0.052***	-0.184***	-0.053***
	(0.009)	(0.006)	(0.009)	(0.006)
log_patent_scope	0.242***	0.116***	0.239***	0.108***
	(0.007)	(0.005)	(0.007)	(0.006)
log_number_of_patents	0.133***	0.046***	0.133***	0.047***
	(0.009)	(0.006)	(0.009)	(0.006)
log_number_of_inventors	0.103***	0.036***	0.105***	0.028***
	(0.006)	(0.004)	(0.007)	(0.005)
US	0.326***	0.168***	0.325***	0.154***
	(0.010)	(0.007)	(0.010)	(0.007)
Constant	-1.214***	-0.361***	-1.221***	-0.436***
	(0.065)	(0.046)	(0.065)	(0.046)
Observations	198,497	110,992	198,497	110,992
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

Table 4.20: PHYSICS (Remove examiner citations)

VARIABLES	Forward Citations	Spillovers	Forward Citations	Spillovers
Eco			0.051***	-0.011***
			(0.004)	(0.003)
Co			0.007	0.061***
			(0.006)	(0.003)
backward_citation	2.184***	0.830***	2.187***	0.834***
	(0.019)	(0.010)	(0.019)	(0.010)
log_timespan	-0.135***	-0.035***	-0.133***	-0.036***
	(0.003)	(0.002)	(0.003)	(0.002)
log_patent_scope	0.240***	0.098***	0.236***	0.099***
	(0.003)	(0.002)	(0.003)	(0.002)
log_number_of_patents	0.104***	0.036***	0.104***	0.036***
	(0.004)	(0.002)	(0.004)	(0.002)
log_number_of_inventors	0.078***	0.033***	0.077***	0.028***
	(0.003)	(0.002)	(0.003)	(0.002)
US	0.565***	0.262***	0.560***	0.256***
	(0.004)	(0.002)	(0.004)	(0.002)
Constant	-1.347***	-0.346***	-1.387***	-0.362***
	(0.024)	(0.014)	(0.025)	(0.014)
Observations	992,337	680,973	992,337	680,973
Time dummies	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Inventor self-citations and applicant self-citations are still removed.

4.7 Conclusion

In this study, we compare the relative strength of eco-innovation and non-eco innovation in terms of their technological support for future inventions and knowledge spillover effects. Additionally, we investigate the differences in quality between global collaborative innovation and non-collaborative innovation, as well as the variations in international knowledge spillover effects. We rely on the PATSTAT database and employ different restrictions and methods to measure the quality of inventions and their international knowledge spillover effects. Our research indicates that eco-innovation has a stronger influence on guiding future inventions and strong knowledge spillover effects compared to non-eco innovation. We find similar results for collaborative innovation. Additionally, we provide a wealth of metrics concerning the comprehensiveness, market value, and complexity of inventions, demonstrating that these variables are correlated with the quality of inventions and their knowledge spillover effects. To ensure the reliability of our results, we conducted extensive sensitivity tests, including focusing on inventions within specific technological fields and making further restrictions on our main measures. These results are crucial for understanding the advantages of eco-innovation and global collaborative innovations in terms of invention quality and knowledge spillover effects. They also provide essential information for policymakers regarding the promotion of eco-innovation and global cooperation.

Specifically, we explored some potential explanations for our findings. First, we found that the novelty, complexity, technological breadth, and potential market value of inventions have an impact on the quality and knowledge spillover effects. The more comprehensive, complex, and applicable to various technological fields an invention is, and the larger the potential market, the stronger its knowledge spillover effects and the better its quality. After controlling for a set of fixed effects, our regression results indicate that the number of backward citations, the number of inventors, patent family size, and technological breadth are all positively correlated with the quality and knowledge spillover effects of inventions (Antoine Dechezleprêtre, Martin, and Mohnen, 2013). On the other hand, the time required for examination is negatively related to the quality and knowledge spillover effects of inventions.

Second, without distinguishing the technological field of the inventions, our results show that compared to non-eco innovation, eco-innovation have a stronger guiding effect on subsequent technologies, as evidenced by the fact that eco-innovations are cited by more future inventions (Antoine Dechezleprêtre, Martin, and Mohnen, 2013). At the same time, the global knowledge spillover effect of eco-innovations is also stronger, manifested in more diverse inventor countries of forward citations for eco-innovations (Antoine Dechezleprêtre, Martin, and Mohnen, 2013). Additionally, our results indicate that global collaborative innovations have a stronger guiding effect on subsequent inventions compared to non-collaborative innovations and are more conducive to global knowledge spillover effects.

These findings offer interesting insights into the roles of eco-innovations and global collaborative innovations in technology development and knowledge spillover effects. These findings offer interesting insights into the roles of eco-innovations and global collaborative innovations in technology development and knowledge dissemination. Eco-innovations often address global challenges, such as climate change and resource scarcity. This may encourage more countries to engage in researching and developing eco-innovations and disseminating this knowledge globally. As eco-innovations often involve globally relevant issues such as environmental protection and sustainable development, they may have a greater impact on subsequent technologies (Arundel and René Kemp, 2009). Global collaborative innovations may involve research teams from multiple countries and regions, which helps to pool more knowledge and skills, thereby improving the quality of innovation outcomes to some extent.

Focusing on specific technical areas, our results also reveal some interesting conclusions. First, our results show the importance of eco-innovation in many technological fields. For most technical fields, the quality and knowledge spillover effects of eco-innovation are significantly better than non-eco innovation. Global collaborative innovation is also more effective than non-collaborative innovation in promoting subsequent technologies. However, in technologies related to human necessities (such as food, water, and housing), eco-innovation demonstrates relatively weaker performance in terms of incentives for subsequent inventions and fostering knowledge spillovers. This may be attributed to the fact that technologies in these fields often focus on meeting basic human needs, and the process of fulfilling these needs might not place as much emphasis on environmental protection and sustainability.

Our results have three policy implications. Our research results have confirmed that while eco-innovation solves environmental problems, it also has a stronger guiding role in future technology, and the cross-border spillover effect of knowledge is more significant. This shows that eco-innovation has great potential in promoting sustainable development, reducing environmental pressure, and promoting international cooperation. Therefore, we should take relevant policy measures to encourage the research and application of eco-innovation in order to achieve global sustainable development goals. Second, encourage international collaboration and knowledge sharing among researchers, institutions, and businesses to accelerate the development of sustainable and environmentally friendly technologies. This will not only strengthen the guiding role of global technological innovation in future technological progress but also promote transnational knowledge spillovers. Finally, policymakers should encourage businesses to find a balance between eco-innovation and production that meets basic human needs. Policymakers should emphasise the importance of incorporating environmental protection and sustainable development principles in the technological innovation process to ensure that basic human needs are met while focusing on ecological sustainability.

Chapter 5

The Impact of Eco-innovation on CO2 Embodied in Trade: Evidence for the Non-linear Relationship between Green Technologies and Carbon Emission

5.1 Introduction

Realising the goals outlined in the Paris Agreement has become an imperative of the highest priority in view of the concerning global climate change. According to the Agreement, the global average temperature rise should be limited to below two degrees Celsius to slow down or prevent catastrophic impacts from climate change (Olhoff and Christensen, 2020). To meet this goal, there is a need for a significant reduction in global greenhouse gas emissions over the next few decades, aiming for net-zero emissions by the middle of this century (Antoine Dechezleprêtre and Kruse, 2022). However, current global commitments and actions to reduce emissions are not sufficient to achieve these goals. Countries efforts in promoting green economies, reducing emissions, and pushing for sustainable development are lacking (Olhoff and Christensen, 2020). Furthermore, reducing pollution not just the responsibility of countries; businesses and individuals also need to take on the task of slowing down climate change. To significantly reduce emissions in the coming decades, there needs to be widespread adoption of low-carbon technologies and infrastructure (Rogelj et al., 2018).

Eco-innovation is widely regarded as an effective mean to address environmental issues, particularly in reducing carbon dioxide emissions (Fei, Rasiah, and Shen, 2014; A. Ahmed, Uddin, and Sohag, 2016; L. Yang and Zhi Li, 2017). Eco-innovation, also known as green technologies, offer the potential to cut carbon emissions without sacrificing economic growth (Acemoglu, Philippe Aghion, et al., 2012). These technologies can be applied across various sectors, including renewable energy, waste management, energy efficiency, and pollution control. Therefore, innovation in clean technologies becomes critical in balancing the transition to a low-carbon footprint with sustained economic growth. To achieve this objective, substantial investments in research and development (R&D) are necessary. This encompasses not only the optimisation and improvement of existing technologies but also the development of new and more efficient low-carbon solutions (Antoine Dechezleprêtre and Kruse, 2022). Such investments can expedite technological maturity, reduce costs, and ultimately encourage broader application.

However, according to Dechezleprêtre (2016), the number of patent applications for low-carbon technologies has declined in recent years. This downward trend might signify that technological innovation, precisely when it is most needed to enhance environmental protection and mitigate climate change, is actually slowing down. Various factors could contribute to this trend, including but not limited to, inadequate research funding, insufficient policy support, and unclear market demand (Acemoglu, Philippe Aghion, et al., 2012).

In the context of globalisation, international trade have increased substantially resulting in environmental issues, notably the increase in carbon emissions. Trade not only involves the cross-border flow of goods and services but also the energy consumption and emissions associated with production and transportation processes (Meng et al., 2018). In recent years, global production chains have become more complex and diversified, introducing new challenges to the reduction of CO2 embodied in trade. Because global supply chains are spread across multiple countries and regions, raw materials, semi-finished, and finished goods often require long-distance transportation to reach end consumers, resulting in increased energy consumption and carbon emissions. This phenomenon is known as 'Carbon dioxide (CO2) Embodied in Trade'. Specifically, when a country exports goods, the carbon emissions embodied in those goods are considered part of that country's carbon output. Conversely, the carbon emissions embodied in imported goods are considered carbon input. Therefore, trade activities actually serve as activities for the "export" and "import" of carbon emissions (Meng et al., 2018).

At the same time, some developed countries, in an attempt to reduce their own carbon emissions and meet domestic environmental standards, opt to relocate high-pollution, high-carbon emission industries to developing countries with more lenient environmental regulations ('pollution haven') (Eskeland and Harrison, 2003). Although this may reduce emissions in the short term for the developed countries, it could potentially result in an increase in global carbon emissions overall. This is because these developing countries often use more outdated and inefficient production methods, leading to higher carbon emissions—a phenomenon known as 'carbon leakage', essentially shifting carbon emissions from one country to another through international trade (Aichele and Felbermayr, 2015). Therefore, to effectively address carbon emission problem along the global value chains (GVCs), we cannot focus solely on reducing domestic carbon emissions; we also need to consider the overall distribution and flow of carbon emissions within global production and trade networks.[1]

While a considerable number of studies have examined the critical role of technological innovation in reducing carbon emissions, there is limited evidence on how eco-innovation can mitigate CO2 emissions embodied in trade activities. This paper aims to explore the relationship between CO2 emissions associated with trade and eco-innovation. Specifically, we employ the intensity of CO2 embodied in trade as a metric for evaluating trade-related carbon emissions and use the number of new green technologies applied in each year as an indicator to assess the level of eco-innovation across countries. Our dataset spans 36 OECD member countries and China, covering the period from 2005 to 2018. OECD member countries are significant drivers of the global economy and play a pivotal role in global carbon emissions. According to statistics, carbon emissions from OECD countries accounted for 35% of global emissions in 2020 (OECD, 2020). Meanwhile, China, a significant emitter, saw its carbon emissions rise by over 60% from 2006 to 2016 (W. Li, Elheddad, and Doytch, 2021). Importantly, most OECD member countries and China are active participants in global climate governance frameworks. Not only have they signed the 1997 Kyoto Protocol, but they also committed to specific emission reduction targets at the 2015 Paris Climate Conference. Countries such as the United States, Germany, the Netherlands, the United Kingdom, and France have been leading in the field of green technological R&D (Elliott, Jabbour, and Y. Su, 2023). Many existing studies illustrate that the application of green technologies has been effective in mitigating carbon emissions among OECD countries

[1]More detailed about 'pollution haven' and 'carbon leakage' will be introduced in literature review part.

(C. Cheng et al., 2021). Besides, to achieve its goals of reaching peak carbon emissions by 2030 and carbon neutrality by 2060, China has formulated various policy measures (X. Zhao et al., 2022). For instance, in its Fourteenth Five-Year Plan and longer-term objectives, China has explicitly emphasised the role of technological innovation in tackling climate change and promoting the adoption of low-carbon technologies in high-emission industries such as coal and construction (He et al., 2020). Thus, focusing on OECD member countries and China effectively addresses both the principal actors in CO2 emissions and trade, as well as the main contributors to eco-innovation. This dual focus allows for a comprehensive understanding of the intersecting relationship of carbon emissions, trade activities, and eco-innovation in sustainability.

Drawing upon existing literature, we postulate a non-linear association between the intensity of CO2 embodied in trade and eco-innovation (W. Li, Elheddad, and Doytch, 2021; C. Cheng et al., 2021). Our empirical results demonstrate that the deployment of new green technologies by exporting countries significantly reduces the intensity of CO2 in their exports. Furthermore, we observe a U-shaped relationship between these variables. This relationship starts with an initial decline in CO2 intensity as the number of new green technologies increases. Yet, we find that the CO2 intensity begins to rise as new applied green technologies continue to increase. This phenomenon could be understood through two perspectives. One possible explanation is the concept of diminishing returns (McFadyen and Cannella Jr, 2004). As the adoption of green technologies becomes more widespread, each additional unit of green technology may result in progressively smaller reductions in CO2 emissions. What may have been an efficient technology at first could become less impactful as it becomes more commonplace.

Another plausible factor is the maturity of the technology itself. Early-stage technologies usually offer substantial emissions reductions as they replace less efficient practices. However, as these technologies mature and gain widespread acceptance, the rate of emissions reduction may taper off. The maturation of technology involves a sequence from its invention or development to widespread acceptance and integration into the market. This progression necessitates navigating several stages, including concept verification, prototype development, market testing, and ultimately, commercialisation. Such a journey is inherently time-consuming as it encompasses continuous technological refinement, market adaptation, and growing acceptance among consumers and businesses. Additionally, the deployment of new technology requires significant financial investments, encompassing research and development costs, marketing expenditures, and the expenses associated with user training. The concept of a technology's "shelf life" refers to the period during which a technology remains cutting-edge before being overtaken by newer, more efficient innovations. For example, for green technologies, initial solutions may significantly reduce pollution, but as technological advances, the environmental impact of these initial solutions may lessen over time. Moreover, businesses often exhibit a cautious approach when adopting new technologies. They assess the costs, potential risks, and compatibility with existing systems before making a commitment. If a new technology, despite its environmental benefits, imposes significant economic burdens or requires substantial investments, companies may adopt a wait-and-see approach or continue to rely on established technologies. This strategy is a reflection of the nonlinear relationship between the adoption of new technologies and the actual reduction in pollution.

Our paper is structured as follows: The second section reviews the existing literature relevant to our study. The third section elaborates on the data sources and outlines the key stylised facts that emerge from the dataset. The fourth section presents our methodological approach. The fifth section focuses on discussing the results obtained from our analyses. The final section offers a conclusion, summarising the key findings and implications of our study.

5.2 Literature Review

Understanding the relationship between international trade and carbon dioxide (CO2) emissions is quite significant, particularly in consideration of the Paris Agreement and the Sustainable Development Goals (SDGs). It is important to acknowledge that trade is associated with a significant proportion, ranging from 25% to 33%, of the total pollution emissions reported worldwide (Copeland, 2021). This statistic illustrates the ecological consequences associated with transnational trade. Several studies have consistently demonstrated similar proportions, particularly in regard to carbon dioxide (CO2) emissions, during study periods. Peters et al. (2011) provided insights into both the direct and indirect effects of global trade patterns on carbon footprints. The study emphasised that commodities that are traded frequently incorporate emissions originating from both the exporting and importing countries. Specifically, industries that are commonly classified as "polluting" or "dirty" frequently have advantages such as decreased tariffs and minimum non-tariff barriers, which encourage their participation in international trade (J. S. Shapiro, 2021). The high degree of accessibility given to these industries that have negative impacts on the environment provides a basis for the common concern that they may intentionally transfer their operations to locations with relaxed regulations on the environment. This finding highlights the serious negative environmental effects trading may cause, underlining the significance of the relationship between trade and protecting the environment. As a consequence, these findings provide valuable guidance for specific environmental policy interventions, emphasising the necessity for modifying regulatory strategies for industries which contribute significantly to international trade (Martin et al., 2014).

Developing countries serve a major part in the increase of global emissions. The statement is supported by data obtained from the World Bank, indicating that the expansion of global emissions is greatly impacted by the rapid processes of industrialisation and urbanisation, particularly in countries such as China and India (Jiao et al., 2022). These environmental shifts are particularly significant in low to middle-income countries, as there is often a shortage of resources and technology to facilitate cleaner manufacturing processes (Kaplinsky and Kraemer-Mbula, 2022). The phenomenon observed in developing countries, whereby they participate in large tariff reductions or seek participation in international trade organisations such as the World Trade Organisation (WTO), brings additional complexity to the current situation (Copeland, 2021). Rodriguez and Rodrik (2000) argue that when countries seek to integrate into the global market, they face changes in their industrial structures, which might result in growing environmental vulnerabilities. Conversely, developed countries have strategically reallocated their environmental responsibilities. The phenomenon of "outsourcing" pollution is easily seen in the consuming behaviours exhibited by wealthy countries. A study conducted by Moran et al. (2018) revealed many industrialised countries had a reduction in their domestic emissions. However, it was found that their consumption-based emissions, which include the outsourced emissions associated with imported goods, displayed an upward trend. As economies become increasingly interconnected, countries can choose to transfer their environmental obligations to their trading partners (Moran et al., 2018). Tukker and Dietzenbacher (2013) demonstrated that corporations have the ability to transfer their operations to countries with fewer strict environmental restrictions in order to avoid stricter regulations in their home countries, which serves as a classic example of the concept known as ‘Pollution Haven’. Another relevant topic for study is the phenomenon known as ‘Carbon Leakage’. This suggests that in the situation when a country reduces its domestic emissions while simultaneously increasing imports of items that are pollution-intensive, there is a possibility that the overall outcome could lead to an increase in global emissions (Aichele and Felbermayr, 2015).

CO2 emissions are closely interconnected with many factors, including economic development and upgrades in technologies. This relationship is effectively represented by the Environmental Kuznets Curve (EKC) (W. Li, Elheddad, and Doytch, 2021). EKC states that during the process of economic growth, a country's environmental degradation, as exemplified by the increase in emissions, initially becomes more severe. However, as the national wealth passes a specific threshold, a reverse becomes visible, marked by a decrease in pollution. The trajectory illustrated displays a distinct inverted U-shaped structure (Dinda, 2004). EKC was first developed to provide a theoretical framework for understanding the relationship between a country's income and its environmental degradation (Cole, Rayner, and Bates, 1997). In the particular context of CO2 emissions, studies typically indicate a positive link with economic growth in the initial phases of a country's development. Emerging economies tend to increase their environmental impact as they seek for rapid modernisation (Amin, Song, and Z. A. Khan, 2022; Lin and Zhou, 2022). However, an important change takes place as these economies reach a more advanced stage of development. As countries transition towards medium or high-income groups, there is an increasing incentive to allocate resources towards cleaner and more sustainable technologies, while simultaneously implementing rigorous environmental regulations (W. Fang, Z. Liu, and Putra, 2022). This shift is not solely a result of a sudden awareness about the environment, but rather a combination of local targets, international obligations, and the economic logic of pursuing sustainable development in the long run (W. Fang, Z. Liu, and Putra, 2022). It is crucial to emphasise the significance of innovation in technology. As countries participate in innovations in technology and adopt environmentally friendly methods, they not only enhance their economic output but also strive to minimise their carbon emissions (Kazaglis et al., 2019; N. Stern and Valero, 2021). In essence, the improvement of technology enables the possibility of attaining economic outputs while concurrently reducing carbon dioxide emissions. Technological upgrading plays a crucial role in the decreasing phase of the EKC, highlighting the potential for achieving a harmonious relationship between economic growth and ecological sustainability (M. Ahmed C. et al., 2022).

From a theoretical point of view, the level of emissions could be affected through three distinct channels; the scale effect, the composition effect, and the technical effect (Grossman and Krueger, 1991; Copeland and M Scott Taylor, 2017). First, the scale effect highlights the positive correlation between economic activity and CO2 emissions. The expansion of production and consumption in an economy is directly associated with a rise in energy consumption and subsequent CO2 emissions, particularly when fossil fuels are the dominant sources of energy (Shahbaz et al., 2019). This correlation suggests that if no mitigative policies are implemented, rapid economic growth may have negative consequences for the environment (Shahbaz et al., 2019). Second, the composition effect can be observed in an economy's transition from agricultural to industrial to service-based phases. Different industries inherently exhibit different levels of carbon footprints. For example, it has been observed that heavy industries have a significantly higher level of carbon intensity compared to the services sector (Golmohamadi, 2022). As economies progress and experience structural changes, the carbon emissions footprint may undergo modifications, depending on the dominating industries. The last one is the technical effect. The use of circular economy concepts and resource efficiency in industrial production processes plays a crucial role in reducing CO2 emissions while simultaneously preserving or even enhancing output levels (Rennings, 2000). Ding, Khattak, and Ahmad (2021) argue that technological progress has the capacity to bring about significant changes by decoupling economic growth from a rise of CO2 emissions, which supports the idea that with the integration of innovations into the production process, economies have the potential to achieve enhanced efficiency, resulting in a reduction of emissions per unit of output (Acemoglu, Philippe Aghion, et al., 2012). Specifically, eco-innovation has the ability to stimulate a transition away from carbon-intensive fossil fuels, resulting in a significant reduction in the carbon emissions associated with the energy industry (Acemoglu, Philippe Aghion, et al., 2012).

However, there is a view that the primary driver of changes in pollution is attributable to fluctuations in emission rates within industries, rather than shifts across various industries (Copeland, 2021). This view challenges the conventional suggestion that reallocation across industries, spurred by comparative advantage, is the dominant reason for environmental change (Davis, 1995). The reason is that the technical effect, representing changes in the methods and processes of production, has a more pronounced influence on emissions than the composition effect, which pertains to shifts across industries (Brunel, 2017; J. S. Shapiro and Walker, 2018). If the pivotal determinant of pollution lies within industries, policy interventions should focus on enhancing production techniques to achieve environmental targets. A large number of studies have focused on the interrelationship between technological innovation and CO2 emissions. Fernández-Amador, Oberdabernig, and Tomberger (2019) investigate the correlation between emissions and economic growth, highlighting the discrepancy between existing emission targets and economic expansion. They emphasise the pressing necessity for accelerated adoption of green technologies. Petrović and Lobanov (2020) also underscore the influence of eco-innovation on CO2 emissions. Through an examination of R&D expenditures and carbon CO2 emissions across 16 members of the OECD from 1981 to 2014, their study underscores the significance of investing in R&D within the realm of eco-innovation as a means to mitigate emissions, and the effects depend on the heterogeneity between countries (A. B. Jaffe, Newell, and Stavins, 2002). Braungardt, Elsland, and Eichhammer (2016) emphasise the significance of deriving long-term advantages from eco-innovation through the analysis of energy demand in the EU countries. Du, P. Li, and Yan (2019) analyse the influence of eco-innovations on CO2 emissions across 71 economies from 1996 to 2012, finding that eco-innovations significantly reduce CO2 emissions only in economies surpassing a high-income threshold. Factors like GDP, urbanisation, industrial structure, trade openness, and energy consumption also play roles in CO2 emissions (Jakob and Marschinski, 2013; Tajudeen, Wossink, and Banerjee, 2018; Du, P. Li, and Yan, 2019). These findings emphasise the need for strategies to decrease the cost of green technology diffusion in lower-income economies.

The discussion on the impact of trade on pollution must address multiple dimensions. It is essential to first clarify that the presence of pollutants in traded goods does not inherently implicate trade as a polluting activity. If production processes are uniform across countries, excluding pollution from transportation and similar processes, the environmental impact remains the same whether products are domestically produced or obtained through trade. However, trade can become a source of increased pollution under specific conditions. For instance, if a country, referred to as Country A, increases its imports from another country, Country B, this demand may prompt an increase in Country B's production levels. Such an increase might result in higher emissions, particularly if the involved production processes are less efficient or adhere to more lenient environmental regulations. This scenario illustrates the 'technique effect,' where disparities in production techniques between trading countries can exacerbate pollution.

Moreover, if Country B specialises in pollution-intensive production due to trade demands, it might experience elevated pollution levels, which could have been mitigated if Country A had produced these goods domestically under stricter environmental standards. Furthermore, assessing the global impact is crucial. An increase in global pollution from trade is contingent not only on the scale of production but also on the composition of traded goods and the relative cleanliness of production techniques in the exporting country. If trade leads to production in locations with inferior techniques due to lax environmental regulations, global pollution may indeed rise. Therefore, the relationship between trade and pollution is intricate, influenced by factors such as production scale, composition of goods, and the effectiveness of production techniques. These considerations highlight the need for international cooperation to harmonise environmental standards and implement cleaner production technologies, ensuring that global trade does not compromise environmental health.

Within the broad literature on eco-innovation and CO2 emissions, there are relatively few studies that look at the non-linear relationship between these two variables (C. Cheng et al., 2021; Y. Chen and C.-C. Lee, 2020). This gap is especially noticeable in the context of bilateral trade. In the real world, which is marked by a deepening of globalisation, the effects of bilateral trade are becoming more and more important. This makes it essential to study these non-linear relationships in order to find ways to control and reduce CO2 emissions caused by trade. In our study of the non-linear relationship between eco-innovation and CO2 emissions in the setting of international trade, the EKC stands out as a key piece of theory. By putting this design into our analytical framework, we look at how eco-innovation and CO2 emissions embodied in trade affect each other. However, it is evident that excessive dependence on economic growth as a sole metric provides an inadequate representation of the intricate relationship between eco-innovation and CO2 emissions. Taking this into account, our model adds other variables such as environmental regulation. For a more complete picture, we also take into account the composition effect in our research. This captures the influence of varying industrial structures in trade on CO2 emissions. Our research aims to provide a comprehensive understanding of the interaction between eco-innovation, bilateral trade, and environmental sustainability, taking into account many aspects and perspectives.

5.3 Data and Stylised Facts

5.3.1 Data

The study aims to investigate the relationship between trade-related CO2 emissions intensity and the number of newly applied green technologies invented by people living in exporting countries. The study focuses on OECD member countries and China for several reasons. This selection is reasoned to capture economic significance, technological advancements, economic diversity, and global influence. The OECD countries and China collectively represent a significant role of global GDP and are major players in international trade. Their trading activities have considerable implications for global carbon emissions, especially China. Besides, some OECD members, such as Germany and the US, are often the leader of technology upgrading, particularly in the area of green technologies. China has also emerged as a significant innovator in green technology. Moreover, the inclusion of both OECD and China introduces an array of diverse economies into the study—from highly developed industrial economies to emerging markets. This heterogeneity permits a better understanding of trade, CO2 emission and eco-innovation.

Our data on CO2 emissions embodied in trade originates from the OECD Embodied CO2 Database. Specifically, the dataset encompasses the CO2 emissions in five categories of trade between OECD member countries and China from the years 2004 to 2018.[2] Data pertaining to innovation is sourced from the PATSTAT database. Our study includes the count of new eco and non-eco simple patent families invented by OECD member countries and China, spanning from 2004 to 2017.[3] We calculate the total number of applied simple patent families involving the inventors living in the exporting or importing countries according to the earliest application year to count innovation, which could avoid the double counting problem.[4] The simple patent families (technologies) could be defined as 'eco' and 'non-eco' according to the IPC green codes.[5] We classify an innovation as an eco-innovation if at least one of the IPC codes associated with the patent is on the green IPC list. In addition to the core explanatory variable of eco-innovation, we also control for GDP per capita. To further alleviate endogeneity concerns, the GDP data is also lagged by one year, with the resulting dataset spanning from 2004 to 2017 for GDP per capita. Beyond this, we control for the trade volume across the five distinct types of trade, as well as the scale and composition effects specific to each trade category.[6]

[2]Five categories include exports in intermediate products, exports in final products, total bilateral exports, domestic value-added (DVA) content of exports and DVA embodied in foreign final demand.

[3]In our regression model, the dependent variable is the intensity of CO2 emissions in trade from 2005 to 2018. To mitigate issues of endogeneity, our core explanatory variable, eco-innovation, is lagged by one year, sourcing data from 2004 to 2017. Concurrently, we control for the actual impact of environmental regulation by using the previous year's trade-related CO2 intensity as a control variable. Therefore, in our descriptive statistics, the data for CO2 intensity in trade ranges from 2004 to 2018, providing a more extensive set of observations.

[4]"Simple Patent Family" is employed to describe a set of interrelated patents that typically originate from a single priority document or the earliest filed patent application. Essentially, a simple patent family encompasses multiple patents filed in disparate jurisdictions that share identical core inventive content and cite the same priority document for their precedence (Antoine Dechezleprêtre, Ménière, and Mohnen, 2017).

[5]Our paper focuses on a complete list of IPC green codes which is generated by the World Intellectual Property Organisation (WIPO): https://www.wipo.int/classifications/ipc/en/ (accessed in October, 2022).eco-innovation could be classified into different green technological fields according to their use and each of these green technical fields is associated with a series of unique green IPC codes (René Kemp and Pearson, 2007).

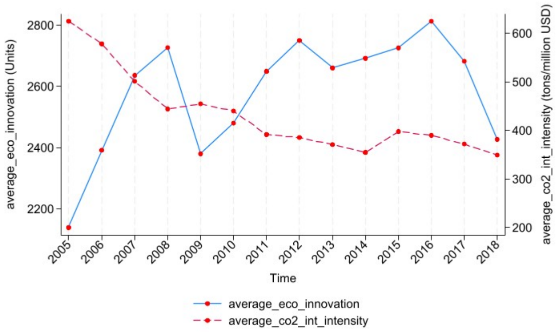
[6]Issues of endogeneity and specific measures for the variables will be elaborated upon in the methodology section of the paper.

Table 5.1: Descriptive Statistics

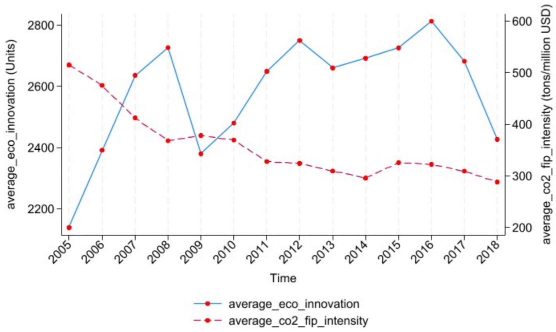
Variable	Obs	Mean	Std. Dev.	Min	Max
Eco-innovation	18648	2582.556	5900.082	1	29721
Non-eco innovation	18648	13790.353	31026.628	52.2	192957.41
Intermediate export ij (USD million)	18648	4182.793	13362.728	0.4	257340.8
Final export ij (USD million)	18648	3086.19	10813.142	0.4	277297.81
Total export ij (USD million)	18648	7268.982	23524.675	0.8	490470.81
DVA export ij (USD million)	18648	5599.635	18749.761	0.6	405475.19
DVA embodied in foreign final demand ij (USD million)	18648	5368.118	18069.074	2.5	453194.31
co2 intensity ij (Intermediate export) (Tons per million USD)	19980	448.491	291.947	0	3339.704
co2 intensity ij (final export) (Tons per million USD)	19980	370.777	221.493	0	3333.333
co2 intensity ij (total export) (Tons per million USD)	19980	413.375	252.214	0	2876.595
co2 intensity ij (DVA export) (Tons per million USD)	19980	366.712	305.606	0	3466.877
co2 intensity ij (DVA embodied in ffd) (Tons per million USD)	19980	386.102	303.794	35.577	3485.508
Scale and composition effect (intermediate export)	18648	302.783	189.192	34.251	1168.004
Scale and composition effect (final export)	18648	256.282	153.987	57.441	1364.756
Scale and composition effect (total export)	18648	281.664	156.099	55.797	1256.968
Scale and composition effect (DVA export)	18648	266.111	141.601	32.075	1003.87
Scale and composition effect (DVA embodied in ffd)	18648	257.801	132.172	68.03	895.475
GDP capita	18648	35719.134	15875.446	4414.173	114862.53

5.3.2 Stylised Facts

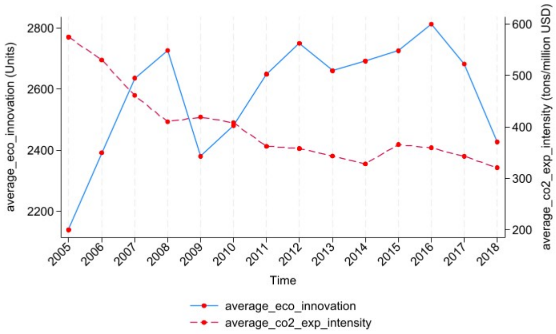
Figure 5.1 focuses on the analysis of the average CO_2 emission intensity (tons per million US dollars) across five different trade dimensions from 2005 to 2018 for OECD countries and China. These figures reveal a clear negative correlation between average trade-related CO_2 intensity and eco-innovation, gauged by the average number of green technologies applications in the exporting countries in each year. Specifically, an increase in the number of new green technology applications per year appears to be associated with a decrease in CO_2 emission intensity. To be noticed, from 2008 to 2009, we observed a decline in the number of new eco-innovations, while there was an increase in CO_2 intensity in trade. This phenomenon can be elucidated through various economic dimensions. First, many countries have launched a series of emission reduction policies and incentives to combat climate change, substantially stimulating eco-innovation and the adoption of clean energy. Eco-innovation generally results in production efficiency gains and the application of cleaner technologies, factors that directly influence the carbon emissions embodied in trade. Technological advancements play a key role here, especially in promoting industrial upgrading and transitioning from high-polluting industries to cleaner, low-carbon ones. The correlation between eco-innovation and CO_2 emissions also mirrors shifts in market mechanisms and consumer preferences. A reduction in the number of eco-innovation applications might imply a weakening in environmental policy rigour, potentially leading to an increase in carbon emissions intensity. Thus, there exists a tight economic linkage between the reduction of CO_2 emission intensity and eco-innovation, reflecting not only technological progress but also the gradual adaptation of the global trade system towards more sustainable and environmentally friendly demands.



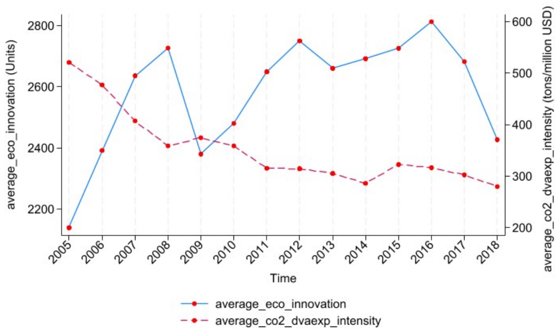
(a) Intermediate



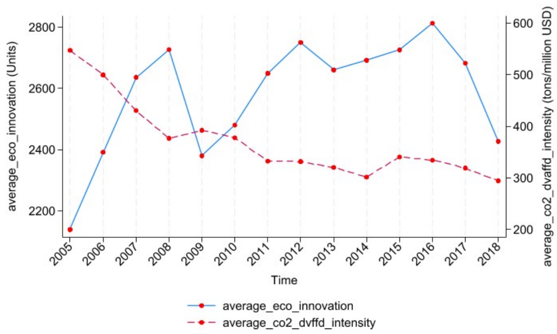
(b) Final products



(c) Total export



(d) DVA embodied exports



(e) DVA embodied in foreign final demand (ffd)

Figure 5.1: Average eco-innovation and average CO2 intensity from 2005 to 2018
Source: Own calculation based on PATSTAT database.

Figure 5.2a shows the top ten countries in terms of the average number of eco-innovation applications from 2004 to 2017 among OECD countries and China. Similarly, Table 5.2 provides a comparative analysis of the leading ten countries based on the quantity of eco-innovations applications in the years 2004 and 2017 individually. The data reveals a consistent set of countries occupying the top ten positions in both the average and individual-year metrics. These countries include the United States, South Korea, Japan, Germany, China, France, the United Kingdom, Canada, the Netherlands, and Italy. Notably, the United States consistently manifests as the top in terms of the number of eco-innovation applications across both the average and the individual years. Among those countries, China emerges as the sole representative from the developing economies.

One of the common among the top-ranking countries is a highly developed educational system that cultivates human capital equipped with the skills requisite for innovation. Advanced skills in science, technology, engineering, and mathematics (STEM) fields act as a catalyst for eco-innovation, which often necessitates cutting-edge scientific and engineering solutions. Besides, policies in these countries, such as tax incentives, grants, and patent protections, also specifically target eco-innovations (Becker, 2015). The propensity of these countries to invest significantly in R&D cannot be overlooked. A positive correlation exists between R&D expenditure and eco-innovation, given that R&D acts as one of the main reasons for new ideas and technological advancements (Arundel and René Kemp, 2009). Moreover, the integration into global supply chains allows these countries to disseminate eco-technologies more effectively, not only within domestic markets but also internationally. China as the lone representative from the developing world is not only attributable to its strategic prioritisation of eco-innovation, fuelled by pressing environmental challenges and the government's policy inclination towards sustainable development (Cai and G. Li, 2018). China's fast industrialisation and participation in global value chains also enhance the collaboration with other developed countries, which fuels eco-innovation aiming at balancing economic growth with ecological sustainability.

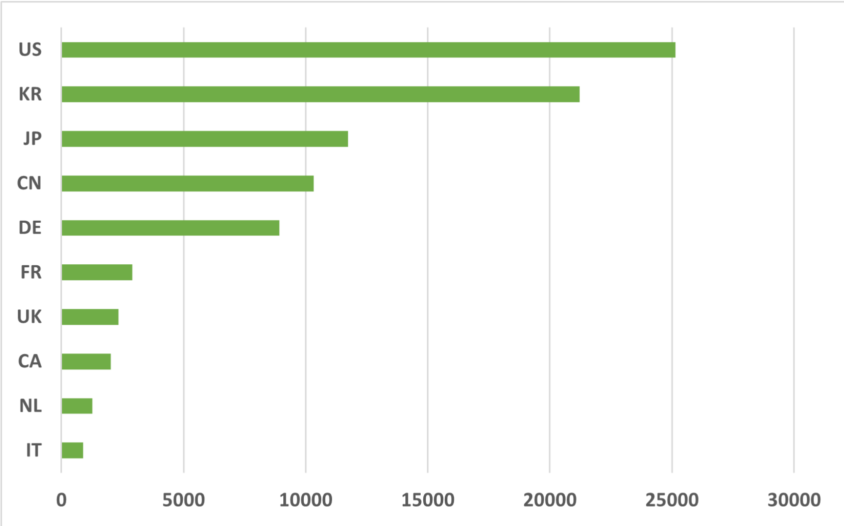


Figure 5.2: Top ten countries of the total number of eco-innovation (average of 2004 to 2017)

(a) *Source*: Own calculations based on the PATSTAT database

Table 5.2: Top ten countries in terms of total number of new eco-innovation applications (2004 VS 2017)

Rank	**Country**	
	2004	**2017**
1	US	US
2	CN	KR
3	KR	JP
4	JP	DE
5	DE	CN
6	UK	FR
7	CA	UK
8	FR	CA
9	NL	NL
10	IT	IT

The observations outlined in Tables 5.3 and 5.4 could be explained through a complex interplay of economic, industrial, and policy factors. Both tables present an analysis of the average CO2 intensity of trade between the years 2005 to 2018, focusing on the top 10 exporting countries and trade country pairs with respect to CO2 emissions per million USD of trade. We found that China's leading role in emissing CO2 from trade. China's leading position in carbon-intensive exports might be attributed to its industrial base, which is heavily skewed towards manufacturing and other high-energy-consuming sectors. China has specialised in sectors that are both labour and energy-intensive, thereby resulting in higher CO2 emissions per unit of trade. Besides, its manufacturing sectors and its long-term role as the "factory of the world" imply that even minor inefficiencies get magnified as China is one of the main global value chain participants and take part in the different production process (Gereffi and J. Lee, 2012).

The tables also show that most of the top ten countries in terms of average CO2 intensity in trade are developing countries. While developed countries are more likely to be CO2 importers than high-intensity CO2 exporters. Developed countries typically have more energy-efficient technologies and production processes, thereby reducing the CO2 intensity of their exports. In contrast, although developing countries are the main body of CO2 emissions in trade, they are not the main body of eco-innovation. For many developing countries, rapid industrialisation and economic growth are immediate priorities, often sidelining environmental considerations. Many developing countries, including China, have a long way to go in adopting cleaner and more efficient technologies and environment regulations. Besides, developed countries, as major consumers of manufactured goods, often transfer carbon-intensive industries to developing countries to avoid stricter environmental regulations (Aichele and Felbermayr, 2015). This could explain why developing countries predominantly feature as high-intensity CO2 exporters, while developed countries appear as importers.

Table 5.3: Top 10 exporting countries in CO2 intensity in different types of trade (average from 2005 to 2018)

Rank	**Intermediate**	**Final product**	**total export**	**DVA export**	**DVA embodied in ffd**
1	CN	CN	CN	CN	CN
2	EE	EE	EE	EE	EE
3	GR	KR	KR	PL	PL
4	TR	CL	PL	KR	GR
5	KR	PL	GR	GR	KR
6	PL	CA	TR	CZ	CZ
7	CZ	CZ	CZ	CA	CA
8	SK	TR	CL	CL	CL
9	CL	GR	CA	TR	SK
10	CA	MX	SK	MX	TR

Table 5.4: Top 10 trading country-pairs in CO2 intensity in different types of trade (average from 2005 to 2018)

Intermediate product	**Final product**	**total export**	**DVA export**	**DVA embodied in ffd**
CN-GR	CN-GR	CN-GR	CN-GR	CN-GR
CN-CL	CL-GR	CN-KR	CN-KR	CN-TR
CN-KR	CN-MX	CN-LV	CN-TR	CN-LV
CN-LV	CN-LV	CN-IL	CN-LV	CN-KR
CN-IL	CN-TR	CN-TR	CN-BE	CN-PT
CN-PT	CN-LT	CN-BE	CN-IL	CN-IL
CN-TR	CN-IL	CN-PT	CN-PT	CN-LT
CN-BE	CN-BE	CN-SI	CN-SI	CN-MX
CN-CA	CN-HU	CN-IT	CN-IT	CN-BE
CN-JP	CN-IT	CN-CA	CN-CA	CN-SI

5.4 Methodology

5.4.1 Endogeneity

In the context of the impact of eco-innovation on CO2 intensity in trade, endogeneity is a critical concern given the potential reciprocal relationship between the two main variables. This bidirectional causality complicates the analysis because one cannot straightforwardly isolate the impact of eco-innovation on CO2 emissions without considering the potential feedback loop from CO2 emissions to eco-innovation. Specifically, eco-innovation could reduce the carbon intensity of trade by countries adopting green technologies. Conversely, higher levels of CO2 emissions may encourage or force firms and governments to invest more in eco-innovation (Antoine Dechezleprêtre and Kruse, 2022). This simultaneity creates a circular problem where the dependent variable (CO2 intensity in trade) could, in turn, be affecting the independent variable (eco-innovation). The relationship may also be subject to confounding by unobserved variables that could affect both eco-innovation and CO2 intensity in trade. For example, economic conditions, geographical location and cultural factors could affect both variables simultaneously. By omitting these factors, the regressions biased estimates (Antoine Dechezleprêtre and Kruse, 2022).

In addressing endogeneity issues of examining the impact of eco-innovation on CO2 intensity in trade, utilising an Instrumental Variable Fixed Effects (IV-FE) model serves as an effective methodology. In this study, we employ the five-year average of new applied non-eco innovation as an instrumental variable for eco-innovation.[7] Indeed, this instrumental variable has gained widespread popularity in the examination of the impact of eco-innovation on carbon emissions

[7]If the new green technologies is first applied in 2005, We calculate the average of the total number of new non-eco innovations between 2001 and 2005 as IVs.

(Carrión-Flores and Innes, 2010). The use of non-eco innovation as an instrument allows us to disentangle the intricate relationship between eco-innovation and carbon emissions. By employing non-eco innovation as an instrument, we introduce an exogenous source of variation that is strongly associated with eco-innovation but remains orthogonal to carbon emissions. Non-eco innovation is widely acknowledged to be closely with eco-innovation. Extensive research illustrates the positive correlation between the number of non-eco innovation and eco-innovation (Triguero, Moreno-Mondéjar, and Davia, 2013; J. A. Zhang and Walton, 2017). The reason here is that a robust innovation system, encompassing both non-eco and eco-innovation, represents a country's overall innovative capabilities, and a country's heightened innovation ability serves as a potent catalyst for fostering eco-innovation. Besides, it is essential to note that while non-eco innovation plays a pivotal role in stimulating eco-innovation, there is limited evidence to suggest that non-eco innovation directly mitigates carbon emissions, especially in the context of international trade. The relationship between non-eco innovation and carbon emissions is complex, as it is mediated by many factors, including the environmental upgrading of industries, energy sources used in production, and consumption patterns (Bag and Pretorius, 2022). Therefore, this IV effectively breaks the bidirectional causal link between eco-innovation and carbon emissions, allowing us to isolate the causal effect of eco-innovation on reducing carbon emissions in trade.[8] Besides, incorporating fixed effects helps to account for time-invariant omitted variables, thereby reducing the omitted variable bias. In this paper, we control for time-fixed effect, country-fixed effect and country-pair fixed effect. We also added more control variables.

[8]The results of the assessment of the validity of the instrumental variable (IV) can be found in the appendix section of this paper.

5.4.2 Theoretical Model

Our research is grounded in the theoretical framework of the IPAT model and EKC, which serves as the foundation for capturing the influence of technological development on environmental pollution (Dietz and Rosa, 1997). This model can be illustrated by equation 5.1:

$$I = \alpha P^{\lambda} A^{\gamma} T^{\beta} \epsilon \tag{5.1}$$

where I is the emission level of a specific pollutant; P is the population size; A captures economic growth and T is the technological factor. In the context of bilateral trade, the model could be shown by equation 5.2:

$$I_{ijt} = \alpha E_{ijt}^{\lambda} A_{it}^{\gamma_1} A_{jt}^{\gamma_2} T_{it}^{\beta_1} T_{jt}^{\beta_2} \epsilon_{ijt} \tag{5.2}$$

Here, i and j denote the exporting country and importing country, respectively. t denotes time. I_{ijt} measures the CO2 intensity in different types of export from country i to country j. In the context of international trade, E_{ijt} captures the trade volume from country i to country j. A_{it} and A_{jt} capture the economic prosperity of i and j, respectively. T_{it} and T_{jt} measure the eco-innovation of i and j. To address endogeneity concerns, we have undertaken specific measures within our research model. We have implemented a lag of one period for the core explanatory variable (T), to alleviate potential endogeneity issues. Simultaneously, we have selected an instrumental variable (IV) for the T variable. Furthermore, recognising the bidirectional causality between economic growth (A) and carbon emissions, we have also incorporated a lag of one period for the economic growth variable (A). Besides, according to the EKC, we include the square terms of the technological factor and economic growth factor in equation 5.3 (Cole, Rayner, and Bates, 1997; Dinda, 2004). Our research focuses mainly on the impact of new eco-innovation on CO2 intensity embodied in trade, which highlights the non-linear effects of green technologies. Therefore, our research model is illustrated as follows:

$$\begin{aligned} lnCO2\_intensity_{ijt} = \alpha_0 + \beta_1 lnECO_{it-1} + \beta_2 lnECO_{jt-1} + \beta_3 lnECO^2_{it-1} + \beta_4 lnECO^2_{jt-1} \\ +\gamma_1 lngdp_{it-1} + \gamma_2 lngdp_{jt-1} + \gamma_3 lngdp^2_{it-1} + \gamma_4 lngdp^2_{jt-1} \\ +\theta lnCO2\_intensity_{ijt-1} + \eta_1 sc_{it} + \eta_2 sc_{jt} + \lambda trade_{ijt} \\ +\epsilon_t + \epsilon_i + \epsilon_j + \epsilon_{ij} + \epsilon_{ijt} \end{aligned} \tag{5.3}$$

α_0 is the constant term, β_1,β_2...η_1,η_2,λ are coefficients of variables. t is the time period, ranging from 2005 to 2018. i is the exporting country and j is the importing country. ϵ_t is the time-fixed effect; ϵ_i and ϵ_j are country-fixed effects. ϵ_{ij} is the country-pair fixed effect, and ϵ_{ijt} is the error term.

$lnCO2\_intensity_{ijt}$ is the logarithm of CO2 intensity in different types of trade. CO2 emission intensity in intermediate goods trade encompasses the early stages of the production chain and usually indicates how many tons of CO2 are emitted per million US dollars of raw materials and semi-finished products exported. This not only incorporates emissions from the combustion of fossil fuels during the production of these intermediate goods but also includes the emissions resulting from transporting these goods to the importing country. In the context of final goods, CO2 intensity typically measures the tons of CO2 emitted per million USD worth of exported final goods. This aggregate accounts for emissions across the upstream sectors in the supply chain, as well as those arising from the transportation of the final goods. The overall trade carbon intensity is an aggregate metric that synthesises the above aspects, offering a comprehensive view of CO2 emissions. The CO2 intensity embodied in the domestic value-added of total exports signifies how much of the CO2 emissions are generated from domestic production activities.

Similarly, CO2 intensity embodied in the domestic value-added of foreign final demand relates to emissions generated from domestic production activities spurred by foreign final consumption.

$lnECO_{it-1}$ and $lnECO_{jt-1}$ are the main explanatory variables that capture the new eco-innovation, first applied between 2005 and 2018, invented by inventors living in exporting or importing countries. They are measured as the logarithm of the count of eco-simple patent families first applied between 2005 and 2018. $lnECO^2_{it-1}$ and $lnECO^2_{jt-1}$ are the square terms that highlight the non-linear relationship between technological growth and CO2 intensity embodied in trade. $lngdp_{it-1}$ and $lngdp_{jt-1}$ capture the economic developing situation measured as the logarithm of GDP per capita. $lngdp^2_{it-1}$ and $lngdp^2_{jt-1}$ are the log of the squared term of GDP per capita (W. Li, Elheddad, and Doytch, 2021). In our regression, $lnCO2\_intensity_{ijt-1}$ is our lagged dependent variable used to control the true environmental regulation effect in real life. In theory, if this indicator is larger, it implies a more relaxed environmental regulatory environment in exporter country i, and consequently, there may be a greater level of future carbon dioxide emissions (Carrión-Flores and Innes, 2010). $trade_{ijt}$ captures different types of trade volume, including exports in intermediate products, exports in final products, total exports, DVA embodied in total export and DVA embodied in foreign final demand.

sc_{it} and sc_{jt} are used to capture the scale and composition effect of country i and country j, which refers to the change in the structure or mix of goods and services in a country's trade. As the composition of industries changes, it can lead to variations in total emissions, even if the technology used remains constant. The emission of CO2 in trade is not solely influenced by advancements in green technology but is also affected by both scale and composition effects. Specifically, if a country transitions its trade from exporting goods produced by high-polluting industries to those produced by low-polluting industries, there can still be a discernible reduction in CO2 emissions.(Cole and Elliott, 2003; Copeland, 2021). As the composition of industries changes, it can lead to variations in total emissions, even if the scale of production and the technology used remain constant. The calculation involves determining the proportion of the overall change in emissions in trade within each country that can be attributed to factors including scale and composition. According to Copeland (2021), the scale and composition effect is structured as follows:

$$scale\ and\ composition\ effect = 100 * \frac{\sum_k Trade_{kt} * CO2intensity_{k2000}}{\sum_k Trade_{k2000} * CO2intensity_{k2000}} \tag{5.4}$$

This equation calculates the change in emissions attributable to both scale and composition effects, normalised by the base year (2000) values for each industry. This equation also gives us a normalised index that can be used to compare changes in emissions in trade due to the scale and composition effects over time and across industries. k is the industry.[9] t is the time period, ranging from 2005 to 2018. $Trade_{kt}$ is the real trade volume that happened in the industry k at time t.[10] $Trade_{k2000}$ is the real trade volume that happened in industry k at the year of 2000. $CO2intensity_{k2000}$ is the CO2 intensity in different types of trade from industry k at the year 2000, equal to the tons per million of USD. A negative association can be expected between the "Scale & Composition" index and CO2 intensity, indicating that an increase in the index value is associated with a decrease in CO2 intensity.[11]

[9] When calculating the scale and composition effect, we consider about 45 industries in total according to the OECD TIVA database.

[10] Trade includes export in intermediate products, export in final products, total exports, DVA embodied in total exports, DVA embodied in foreign final demand.

[11] The reason will be illustrated in the empirical finding section.

5.5 Empirical Findings

Within this section, we shall proceed to present the outcomes of the regression analysis. The IV-FE (Instrumental Variable - Fixed Effects) model is utilised to effectively address endogeneity issues related to our main independent variable. The findings related to OECD members and China are considered as the basis for our analysis. Moreover, with the exclusion of China and the exclusive emphasis on the OECD, we are able to compare the regression outcomes with the baseline results. The results of the first-stage regression and the validity tests for the instrumental variables are provided in the appendix for further examination.

Table 5.5 provides a comprehensive analysis of the association between new applications of eco-innovation and CO2 intensity within various trade frameworks. Upon analysis of the regression outcomes across various columns, it becomes evident that there exists a U-shaped correlation between the CO2 intensity in trade and the eco-innovation of the exporting country. Specifically, the coefficient for new eco-innovation of the exporting country is negative, indicating that an increase in green technological advancements in the exporting country is associated with a reduced CO2 intensity manifested in its exports. For example, Column 4 and 6 show that a 10% increase in the applications of new eco-innovation invented by exporting countries will reduce the CO2 intensity in final product export and CO2 intensity in total exports by about 1.94% and 0.9%, respectively. Nevertheless, the positive coefficient for the squared term of eco-innovation of exporting countries adds intricacy. The positive signs mean that the additional advantages of new eco-innovation in terms of CO2 intensity reduction become less significant, which highlights the importance of the green technologies that have been already used in real life. Indeed, it is worth noting that, additional advancements in eco-innovation may unexpectedly correspond with a rise in CO2 intensity embodied in trade.

The implementation of an environmentally friendly technology typically displaces an outdated and less effective alternative. For example, the initial shift from coal-based energy to solar photovoltaic systems can lead to significant decreases in carbon emissions as a result of the notable gap in their respective carbon footprints. Besides, the notion of diminishing marginal returns becomes apparent when the industries become increasingly flooded with green technologies. The adoption of each new green technology typically results in a diminishing reduction in carbon emissions. Furthermore, like many other innovations, green technologies go through a technological lifespan. During its early stages of development, a technology exhibits significant potential for improvement and optimisation. Nevertheless, once it reaches its peak, additional improvements become increasingly minimal due to fundamental physical or theoretical limitations. Consider, for example, solar cells, which are subject to the limitations imposed by the Shockley-Queisser limit. This constraint makes significant advancements in efficiency increasingly unlikely when the technology reaches a more mature stage. Finally, the early implementation of green technology may occur on a limited scale, accompanied by relatively small-scale infrastructure and energy requirements. However, when the technology is expanded to adjust to additional demands, the infrastructure and operations might experience amplification, which leads to the need for greater energy inputs. The potential consequences of this growth could accidentally undermine the intended carbon reduction advantages associated with the technology. In conclusion, the carbon intensity reduction in exports, related to the adoption of green technology, can be defined as a U-shaped curve. The early stages of the process exhibit a significant reduction in carbon dioxide intensity. Nevertheless, when technology becomes more widespread and develops more within exporting countries, the rate of decline may slow down, which could result in a relative increase in emissions. This highlights the necessity for policymakers and economists to not alone encourage technological breakthroughs, but also to maintain a close watch on the possible persistent obstacles associated with the growth and advancement of these solutions.

The correlation between the GDP per capita of the exporting country and the CO2 intensity in its exports, which exhibits an inverse U-shaped pattern, is consistent with the principles of the EKC hypothesis (Y. Chen and C.-C. Lee, 2020; W. Li, Elheddad, and Doytch, 2021). The EKC theory states that as a country's stage of economic development progresses, as measured by GDP per capita, there is an initial increase in the deterioration of the environment. However, this degradation eventually reaches a peak and starts to decline as the country's GDP per capita continues to rise. Specifically, When examining our findings through the EKC, it becomes evident that in the early phases of economic development, nations may place a higher emphasis on achieving economic growth rather than taking into account environmental issues, shown as the positive correlation between the increase in GDP per capita and the increased CO2 intensity of exports. As exporting countries reach high levels of economic prosperity, there is a tendency for their focus to transition towards the adoption of green technologies, and the implementation of more stringent environmental regulation. These changes, prompted by increased economic prosperity, lead to a subsequent reduction in CO2 intensity, thereby depicting the downward-sloping segment of the inverse U-shaped curve.

The variable $lnCO2\_intensity_{ijt-1}$ serves as the lagged dependent variable in our analysis, allowing us to account for the influence of previous levels of carbon dioxide intensity. This control variable is employed to mitigate the impact of actual environmental regulations on the observed outcomes. The reason for including this element arises from the underlying assumption that prior levels of CO2 intensity can have a lasting impact on future levels (Carrión-Flores and Innes, 2010). This influence is attributed to the persistence of established industrial practices and the long-lasting impact of past environmental restrictions (Carrión-Flores and Innes, 2010). Moreover, by the inclusion of a lagged effect control, we can enhance the reliability of our analysis in isolating the effects of various independent variables. The empirical findings of our study indicate a positive correlation between the lagged CO2 intensity and the future CO2 intensity in the context of trade. This indicates a persistence effect: a higher CO2 intensity in one period tends to propagate and manifest in elevated levels in subsequent periods. Those results also underscore the significance of early interventions and regulatory mechanisms in shaping future environmental outcomes in the realm of trade.

In addition to controlling the export volume, we also control the scale and composition effect for both the exporting country and the importing country. As the index goes up, there is a corresponding decrease in the CO2 intensity in trade. The carbon intensity of a country's exports is influenced by the unique features of its principal exported goods within the context of global trade. Consider, for example, a hypothetical scenario involving a country that primarily engaged in the exportation of coal during the year 2000. Due to the substantial carbon emissions resulting from coal mining and combustion, it is expected that the carbon intensity of the country's exports will be inherently heightened throughout this timeframe. In the future, specifically in year t, the country has successfully shifted its export portfolio to prioritise software. Significantly, despite the potentially large carbon emissions linked to software manufacturing in the year 2000, it is worth noting that the software business possesses an intrinsic lower carbon intensity in comparison to industries reliant on fossil fuels. Therefore, the rise in software export quantities, along with a corresponding increase in carbon dioxide emissions, indicates a process of industrial upgrading inside the country's trade framework. The outcome of this transition towards a low-carbon-intensive sector is a reduction in the overall carbon intensity of exports, regardless of the potential increase in absolute emissions and exports from the software industry, which could also increase the index.[12]

The results presented in Table 5.6 exclusively apply to the member countries of OECD, with the exception of China. The results align with the findings drawn from Table 5.5, emphasising a U-shaped correlation between the number of eco-innovations in the exporting country and the carbon intensity embodied in its exports. It is worth noting that when only analysing OECD countries, the eco-innovation of importers has a significant impact in reducing the carbon intensity associated with imports. OECD members exhibit a propensity towards aligning their environmental and trade policies, often engaging in collaborative eco-innovation. Within the framework of trade interactions restricted to the OECD countries, it is expected that substantial technical spillovers will arise (Keller, 2010). If the importing country serves as a trade partner with strong R&D ability, it is possible that its trading partners may have the opportunity to adopt these innovations. As a result, this might lead to a reduction in their overall greenhouse gas emissions. Simultaneously, the coexistence of mutual environmental regulations and comparable levels of economic development indicates that both countries might be at similar stages of development. Furthermore, it is important to highlight that among the member countries

[12]However, the complexities around carbon intensity arise when there is simultaneous expansion across various industries. For example, if the export levels of a sector with high carbon intensity, such as coal, increase in combination with a sector with low carbon intensity, such as semiconductors, the overall change in carbon intensity depends on the respective contributions of both sectors and their intrinsic carbon intensities. However, for OECD countries as well as China, the decrease in carbon intensity shown in their trade matrix can be argued to be mostly due to industry upgrading rather than just sectoral development. In recent decades, there has been a shift in these economies away from primary dependence on conventional manufacturing towards a more knowledge-intensive and service-oriented economic structure. In particular, the majority of OECD members consist of developed countries. Additionally, China has experienced a transformation in its manufacturing approach, leading to a transition towards sectors that involve greater value-added. This shift is gradually replacing conventional industries characterised by high emissions and low value-added (W. Li, Elheddad, and Doytch, 2021).

of OECD, there is a significant and increasing desire for products that are both environmentally friendly and sustainable (Brécard et al., 2009). The existence of a strong potential for eco-innovation indicates the importance that an importing country places on environmental protection. As a result, exporters make adjustments to their products in order to comply with sustainability standards and preferences that are prominent in these countries.

Table 5.5: Second stage results of OECD + China

	1	2	3	4	5	6	7	8	9	10
VARIABLES	**Intermediate**		**Final**		**Total export**		**dvaexp**		**dvaffd**	
lag1_ECO_i	-0.049**	-0.054**	-0.183***	-0.194***	-0.088***	-0.090***	-0.129***	-0.132***	-0.084***	-0.092***
	(0.022)	(0.022)	(0.024)	(0.024)	(0.020)	(0.020)	(0.027)	(0.027)	(0.020)	(0.020)
lag1_ECO_j	-0.023	-0.023	-0.049**	-0.049**	-0.022	-0.022	-0.038	-0.037	-0.001	-0.002
	(0.024)	(0.024)	(0.021)	(0.020)	(0.021)	(0.021)	(0.030)	(0.030)	(0.021)	(0.021)
lag1_ECO_i_2	0.011***	0.012***	0.019***	0.020***	0.013***	0.013***	0.018***	0.018***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lag1_ECO_j_2	-0.001	-0.001	0.005***	0.005***	0.000	0.000	-0.000	-0.000	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lag1_GDP_capita_i	0.794***	0.954***	0.549***	0.619***	0.699***	0.729***	0.954***	0.998***	0.933***	0.992***
	(0.139)	(0.142)	(0.138)	(0.138)	(0.132)	(0.134)	(0.181)	(0.182)	(0.143)	(0.142)
lag1_GDP_capita_j	-0.026	-0.014	-0.026	-0.025	-0.112	-0.119	-0.230	-0.240	-0.149	-0.142
	(0.165)	(0.167)	(0.133)	(0.133)	(0.154)	(0.154)	(0.210)	(0.210)	(0.141)	(0.141)
lag1_GDP_capita_i_2	-0.045***	-0.052***	-0.030***	-0.032***	-0.038***	-0.039***	-0.050***	-0.051***	-0.047***	-0.048***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.007)	(0.007)
lag1_GDP_capita_j_2	0.001	0.000	0.003	0.002	0.006	0.007	0.014	0.014	0.013*	0.012*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)
lag1_CO2_intensity_ij	0.513***	0.510***	0.515***	0.513***	0.526***	0.526***	0.547***	0.545***	0.568***	0.568***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)
Trade_ij	-0.007	-0.005	-0.006	-0.004	-0.015***	-0.015***	-0.043***	-0.042***	-0.097***	-0.089***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)
Scale and composition effect i		-0.028***		-0.025***		-0.017***		-0.022***		-0.046***
		(0.003)		(0.004)		(0.004)		(0.005)		(0.005)
Scale and composition effect j		-0.002		0.001		0.004		0.006		-0.002
		(0.004)		(0.004)		(0.004)		(0.005)		(0.004)
eco-innovation threshold level (i)	9.275	9.488	123.444	127.740	29.507	31.866	35.993	39.121	16.445	21.470
Constant	-0.172	-0.960	0.778	0.493	0.373	0.286	-0.660	-0.788	-1.595	-1.817*
	(1.078)	(1.085)	(0.932)	(0.932)	(1.005)	(1.011)	(1.395)	(1.396)	(1.004)	(1.003)
Observations	18,529	18,529	18,529	18,529	18,529	18,529	18,529	18,529	18,529	18,529
R-squared	0.943	0.944	0.943	0.943	0.949	0.949	0.946	0.946	0.968	0.968
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Countrypair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5.6: Second stage results of OECD countries

	1	2	3	4	5	6	7	8	9	10
VARIABLES	**Intermediate**		**Final**		**Total export**		**dvaexp**		**dvaffd**	
lag1_ECO_i	-0.057***	-0.055**	-0.178***	-0.189***	-0.097***	-0.102***	-0.145***	-0.150***	-0.097***	-0.104***
	(0.022)	(0.022)	(0.024)	(0.023)	(0.019)	(0.019)	(0.025)	(0.025)	(0.018)	(0.018)
lag1_ECO_j	-0.062***	-0.062***	-0.039*	-0.038*	-0.052***	-0.050**	-0.092***	-0.090***	-0.036*	-0.036*
	(0.023)	(0.023)	(0.021)	(0.020)	(0.020)	(0.020)	(0.029)	(0.029)	(0.020)	(0.020)
lag1_ECO_i_2	0.007***	0.008***	0.012***	0.013***	0.009***	0.009***	0.015***	0.016***	0.013***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
lag1_ECO_j_2	0.002	0.002	0.001	0.001	0.002	0.002	0.003	0.003	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lag1_GDP_capita_i	1.706***	1.771***	1.718***	1.806***	1.717***	1.743***	1.933***	1.953***	1.719***	1.827***
	(0.181)	(0.180)	(0.182)	(0.181)	(0.166)	(0.166)	(0.240)	(0.240)	(0.171)	(0.173)
lag1_GDP_capita_j	0.518**	0.530***	0.337*	0.343*	0.333*	0.325*	0.522**	0.523**	0.193	0.228
	(0.205)	(0.205)	(0.179)	(0.176)	(0.184)	(0.183)	(0.234)	(0.234)	(0.161)	(0.162)
lag1_GDP_capita_i_2	-0.089***	-0.092***	-0.086***	-0.089***	-0.087***	-0.088***	-0.097***	-0.097***	-0.085***	-0.088***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.012)	(0.012)	(0.008)	(0.008)
lag1_GDP_capita_j_2	-0.025**	-0.025**	-0.014*	-0.015*	-0.015	-0.014	-0.022*	-0.022*	-0.003	-0.005
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.008)	(0.008)
lag1_CO2_intensity_ij	0.515***	0.514***	0.511***	0.509***	0.530***	0.530***	0.551***	0.550***	0.573***	0.573***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
Trade_ij	-0.007	-0.006	-0.008	-0.005	-0.017***	-0.016***	-0.044***	-0.043***	-0.097***	-0.089***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)
Scale and composition effect i		-0.024***		-0.024***		-0.011***		-0.022***		-0.047***
		(0.004)		(0.005)		(0.004)		(0.005)		(0.005)
Scale and composition effect j		-0.002		0.001		0.004		0.008		-0.004
		(0.004)		(0.004)		(0.004)		(0.006)		(0.005)
eco-innovation threshold level (i)	58.641	31.109	1663.479	1435.446	218.960	289.069	125.629	108.581	41.711	76.198
Constant	-7.466***	-7.795***	-6.902***	-7.297***	-6.983***	-7.054***	-9.330***	-9.381***	-7.222***	-7.842***
	(1.363)	(1.361)	(1.254)	(1.238)	(1.216)	(1.215)	(1.652)	(1.652)	(1.175)	(1.184)
Observations	17,521	17,521	17,521	17,521	17,521	17,521	17,521	17,521	17,521	17,521
R-squared	0.932	0.932	0.930	0.930	0.939	0.939	0.936	0.936	0.962	0.962
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Countrypair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.6 Conclusion and Policy Implications

Trade, an essential component of global economic interaction, has a complex relationship with environmental issues, particularly the emissions of CO2. The cross-border movement of products and services involves substantial use of energy, leading to the generation of substantial carbon footprints (Copeland, 2021). As the requirement to address climate change gets more pressing, there's a growing emphasis on analysing the environmental consequences of trade. It highlights the necessity to determine environmentally friendly techniques to promote economic growth while reducing harm to the environment. Eco-innovation, which can be described as the development and implementation of environmentally friendly technologies, presents a promising prospect for improving productivity and trading effectiveness, while also mitigating carbon emissions. Eco-innovations attempt to link economic activity with sustainable principles in order to separate economic progress from harmful environmental consequences. While prior research has established the efficacy of eco-innovation in mitigating carbon emissions, there remains a need for more investigation into the connection between new green technologies and the actual carbon emissions associated with trade (L. Yang and Zhi Li, 2017; Y. Chen and C.-C. Lee, 2020; W. Li, Elheddad, and Doytch, 2021). This study examines the correlation between new eco-innovation and the CO2 intensity associated with various forms of trade across members of the Organisation for OECD countries and China. The findings of this research highlight the presence of a nonlinear relationship between these variables.

Incorporating the IVFE model, our study aims to mitigate endogeneity issues related to the main explanatory variable. Our findings indicate a negative correlation between the new eco-innovations of the exporting country and the CO2 intensity in its exports, with a specific focus on the member countries of the OECD and China. The results of our study reveal a U-shaped correlation between the eco-innovations and the CO2 intensity embedded in trade. During the early phases, the growth of green technology is accompanied by a reduction in CO2 intensity, highlighting the immediate positive effects of adopting green technologies on the environmental impact of trade. These potential advantages may arise from enhanced energy efficiencies, the implementation of sustainable practices, and the reduction of waste provided by early eco-innovations. Nevertheless, it becomes that the CO2 intensity embodied in trade begins to rise again, despite continuing developments in eco-innovation. The increase in question can be attributed to a range of factors, including the existence of saturation effects where the incremental advantages of further eco-innovations are reduced. The U-shaped pattern observed highlights the significance for economists to not only promote new technologies but also to closely monitor the potential persistent barriers connected with the implementation and progress of these solutions in mitigating CO2 emissions.

By narrowing our research to solely concentrate on member countries of OECD, our findings indicate that eco-innovation of the importing side also has a significant impact on reducing the CO2 intensity embodied in imports. This implies that the green activities undertaken by exporting countries are of the greatest significance, while the environmental strategies and adoption of green technologies by importing countries have a substantial impact on the carbon footprint associated with trade. It highlights the significance of the demand side, specifically the need for environmentally friendly products in the countries that import them. The emphasis on the production of eco-innovative products by importing countries serves as an additional incentive for exporting countries to match their manufacturing processes with environmentally sustainable principles.

As revealed by the U-shaped relationship between eco-innovations and CO2 intensity embodied in trade, policymakers should be vigilant in supporting and guiding the use of new eco-innovation. Encourage exporting industries to not only adopt but also optimise their use of green technologies. Avoiding saturation effects and ensuring that each incremental eco-innovation offers tangible carbon reduction benefits is paramount. It's crucial to understand that more isn't always better; what matters is the effective implementation of green technologies. Besides, after excluding China, the significant influence of importing countries' eco-innovation on reducing CO2 intensity embodied in trade underscores the power of demand. Policymakers in importing countries should stimulate demand for eco-innovative products through public awareness campaigns, incentives, and potential regulatory mandates. This will not only reduce the domestic carbon footprint but will also incentive exporting countries to align their production with green standards. Finally, given the interconnectedness of the global trade system, it's essential to foster collaborations and partnerships among countries, both exporting and importing. Policymakers should work towards international agreements or frameworks that champion eco-innovations across the entire supply chain, ensuring that both sides of the trade towards a sustainable future.

While our research provides a view on general, dissecting this relationship by sector could yield different insights. For instance, how does the relationship between eco-innovation and CO2 intensity embodied in trade manifest in energy-intensive sectors versus service-oriented sectors? We could further expect a five-year (10-year) delay as it takes time for industries to adopt new technologies and update their old technologies. Besides, it might be valuable to study the lifecycle impacts of various green technologies adopted in trade. Not all eco-innovations are created equal, and some might have more significant upfront carbon costs but lower long-term emissions, while others might offer immediate benefits but lesser long-term advantages. Understanding these lifecycle impacts can help in formulating strategies to maximise CO2 reduction in trade. Furthermore, in addition to observing newly applied green technologies, the role of technology stocks in reducing emissions in trade also deserves further research and discussion. These are potential areas for future research.

Chapter 6

Conclusions

This thesis comprises four studies that make contributions to the existing body of research on greening global value chains. After an overview in Chapter One, the second chapter examines the general patterns in eco-innovation and emphasises the worldwide trends in eco-innovation and collaborative innovation. Chapter three investigates the relationship between global value chains (GVCs) and international technological collaboration, with a specific focus on collaborative eco-innovation. The results find a clear link between GVC participation and collaborative eco-innovation, highlighting the importance of bilateral trade in facilitating collaborative eco-innovation in the context of GVCs. Further results show that cooperation along GVCs can serve as a channel for enhancing eco-innovation for both developed and developing countries, giving opportunities to some developing countries that have challenges in developing green technologies independently.

The subsequent chapter explores the impact of collaborative eco-innovation on future technology. Chapter four of the study focuses mainly on the quality and knowledge spillover effect of eco-innovation and collaborative innovation. This study examines the influence of patent families related to eco-innovation on subsequent innovation and the potential for knowledge spillover across international borders by employing forward citation data as a measure. The findings of the study suggest that eco-innovation has a positive impact on the development of future technologies and leads to greater cross-border knowledge spillovers when compared to non-eco innovation. Additionally, patent characteristics such as backward citations, patent family size, and the number of researchers are found to influence patent quality and knowledge diffusion. The study further reveals that in comparison to non-collaborative innovation, collaborative innovation exhibits higher quality. This is manifested by a higher count of forward citations, indicating their enhanced capacity to provide better guidance for future inventions and generate superior global knowledge spillover effects.

In the fifth chapter, a study is conducted on the relationship between eco-innovation and the carbon dioxide emissions that are linked to global trade. The study concentrates on countries that are members of the OECD as well as China. The findings indicate that eco-innovations originating from countries engaged in exporting activities have a substantial impact on reducing the carbon dioxide (CO2) intensity associated with exporting. This highlights the positive effects of green technology in promoting environmentally sustainable practices within GVCs. Nevertheless, the research highlights a U-shaped relationship, indicating that the potential environmental benefits may decrease as further eco-innovation is implemented. Moreover, when considering exclusively OECD member countries, the eco-innovation of both exporting and importing countries has a role in reducing the environmental consequences of trade, highlighting the significant importance of the demand side.

In brief, the main objective of chapter three is an analysis of the stimulating impact of GVCs on international technological collaboration, specifically highlighting collaborative eco-innovation. The results emphasise the important role of GVCs in promoting international technological collaboration, specifically in the context of collaborative eco-innovation. In Chapter Four, the study of eco-innovation and collaborative innovation focuses on their quality and knowledge spillover effects. The findings of this analysis demonstrate the beneficial influence of innovation on the direction of future technologies and the facilitation of cross-border knowledge transfer. In the fifth chapter, a study is conducted on the relationship between eco-innovation and the CO2 intensity that is present in trade. This research highlights the advantages of employing eco-innovation in the process of making GVCs more environmentally friendly. Additionally, it highlights the possibility of encountering diminishing returns as the quantity of eco-innovation initiatives grows. Every chapter within the work explores the policy implications associated with eco-innovation and international collaboration, ultimately highlighting the importance of these factors in facilitating the green transition within GVCs.

Based on the empirical results presented in this paper, several key policy implications emerge. Firstly, policymakers should take relevant measures to encourage the research and application of eco-innovation in order to achieve global sustainable development goals. Policies aimed at stimulating international technological collaboration, particularly in the context of collaborative eco-innovation, should be designed with a global perspective. Given the complex nature of the global trading network and the increasing role of developing countries in GVCs, it is essential to foster international cooperation between developed countries and developing countries, considering developing countries often face challenges in independently developing green technologies due to limited domestic innovation capabilities, slow industrial upgrading, and inadequate patent protection systems. Second, policymakers should consider encouraging joint R&D programs between developed and developing countries. Facilitating collaborative eco-innovation through GVCs could give an opportunity for developing countries to green their export, as knowledge sharing among researchers, institutions, and businesses could accelerate the development of sustainable and environmentally friendly technologies. Finally, policymakers should be vigilant in supporting and guiding the use of eco-innovation. Encourage exporting industries to not only adopt but also optimise their use of green technologies. It's crucial to understand that more isn't always better; what matters is the effective implementation of eco-innovation.

The primary constraint now under consideration relates to the inherent challenges associated with our data collecting process. The foundation of our study is mostly based on macro-level data that is distinct to each country. The inclusion of trade and pollution data at the firm level will greatly enhance the amount of detail and accuracy in our investigation on the relationship between eco-innovation and pollution. Moreover, this approach would facilitate a more nuanced comprehension of the varying effects of eco-innovation within particular types of firms. The inclusion of a comprehensive degree of information is crucial in order to extract practical insights and make recommendations that specifically address the distinct requirements and obstacles faced by various sectors. Lastly, in capturing the CO2 intensity embodied in trade, our dataset reflects the CO2 emissions resulting from the combustion of fossil fuels during trade activities. Regrettably, we are unable to ascertain the proportion of clean energy utilised in trade operations. Consequently, this precludes our ability to directly analyse the tangible impacts by eco-innovation within the GVCs, despite we control for the scale and composition effects.

Future research in the realm of trade and its environmental implications presents several promising avenues. Firstly, the pressing need to address climate change necessitates a deeper examination of environmentally friendly techniques to balance economic growth and environmental sustainability. Focusing on the connection between green technologies and actual carbon emissions associated with trade, particularly in different sectors, could yield valuable insights. Research might explore how eco-innovation impacts CO2 intensity in energy-intensive sectors compared to service-oriented sectors, shedding light on sector-specific strategies for reducing emissions. Additionally, investigating the dynamics of collaborative eco-innovation within GVCs and its implications for developing and developed countries would provide valuable insights for policymakers. Future studies might focus on the effectiveness of joint R&D programs between countries and the potential barriers and facilitators for international technological cooperation. In conclusion, future research should aim to deepen our understanding of the complex relationship between trade, eco-innovation, and environmental sustainability. Sector-specific analyses, investigations into eco-innovation mechanisms, and studies on international collaboration within GVCs can inform policymakers and stakeholders in their efforts to promote green technologies, reduce carbon emissions, and work toward a more sustainable global value chain.

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Appendix A

Appendix to Chapter Two

A.1 The abbreviations of economies included in the report

Abbreviations (two-letter codes)	Economy names
AR	Argentina
AT	Austria
AU	Australia
BE	Belgium
BG	Bulgaria
BR	Brazil
BY	Belarus
CA	Canada
CH	Switzerland
CL	Chile
CN	China
CO	Colombia
CZ	Czechia
DE	Germany
DK	Denmark
ES	Spain
FI	Finland
FR	France
UK	United Kingdom
GR	Greece
HK	Hong Kong, China
HR	Croatia

HU	Hungary
IE	Ireland
IL	Israel
IN	India
IT	Italy
JP	Japan
KR	Republic of Korea
MD	Republic of Moldova
MX	Mexico
MY	Malaysia
MX	Mexico
NL	Netherlands
NO	Norway
NZ	New Zealand
PH	Philippines
PL	Poland
PT	Portugal
RO	Romania
RU	Russian Federation
SA	Saudi Arabia
SE	Sweden
SG	Singapore
SI	Slovenia
SK	Slovakia

TH	Thailand
TR	Türkiye
TW	Taipei,China (Taiwan, Province of China)
UA	Ukraine
US	United States
ZA	South Africa

Source: Authors' own collection based on the work by the International Organization for Standardization (ISO) and Asian Development Bank (ADB).

Appendix B

Appendix to Chapter Three

B.1 Trade links

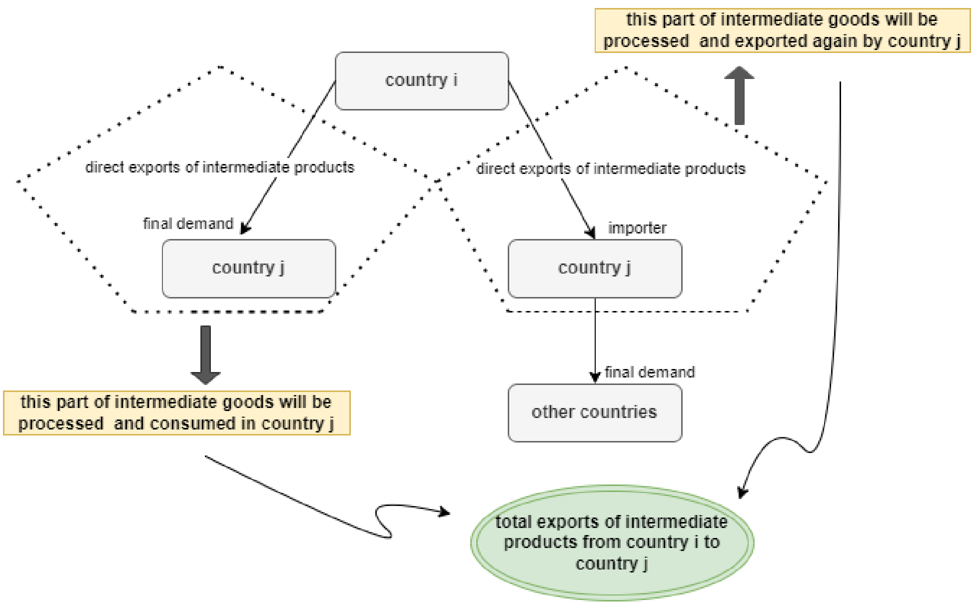


Figure B.1: Exports of intermediate products

Source: Own work based on the instructions of OECD TiVA database

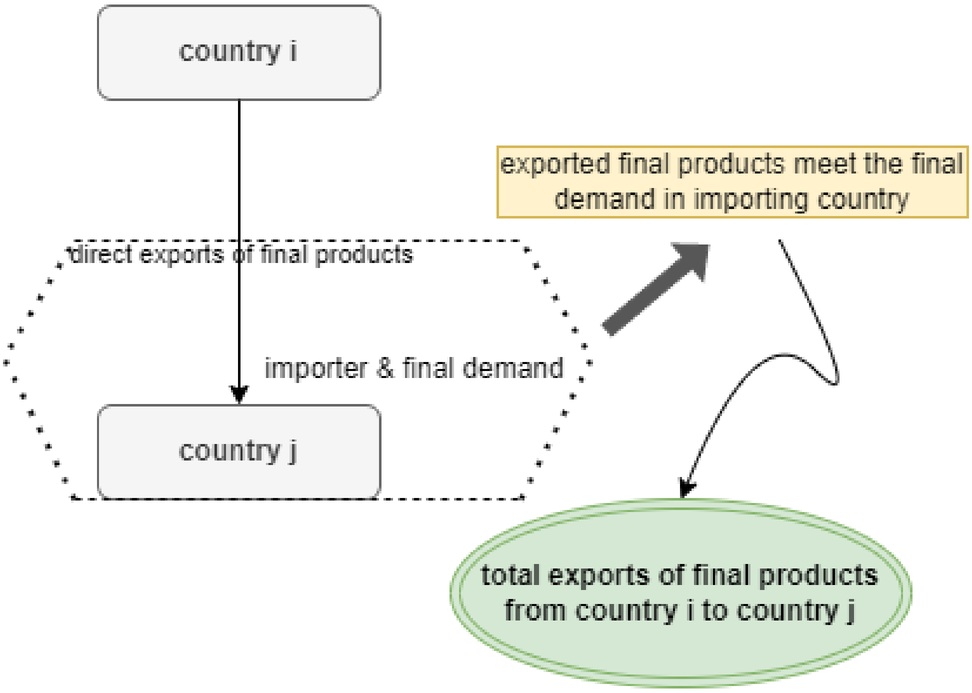


Figure B.2: Exports of final products

Source: Own work based on the instructions of OECD TiVA database

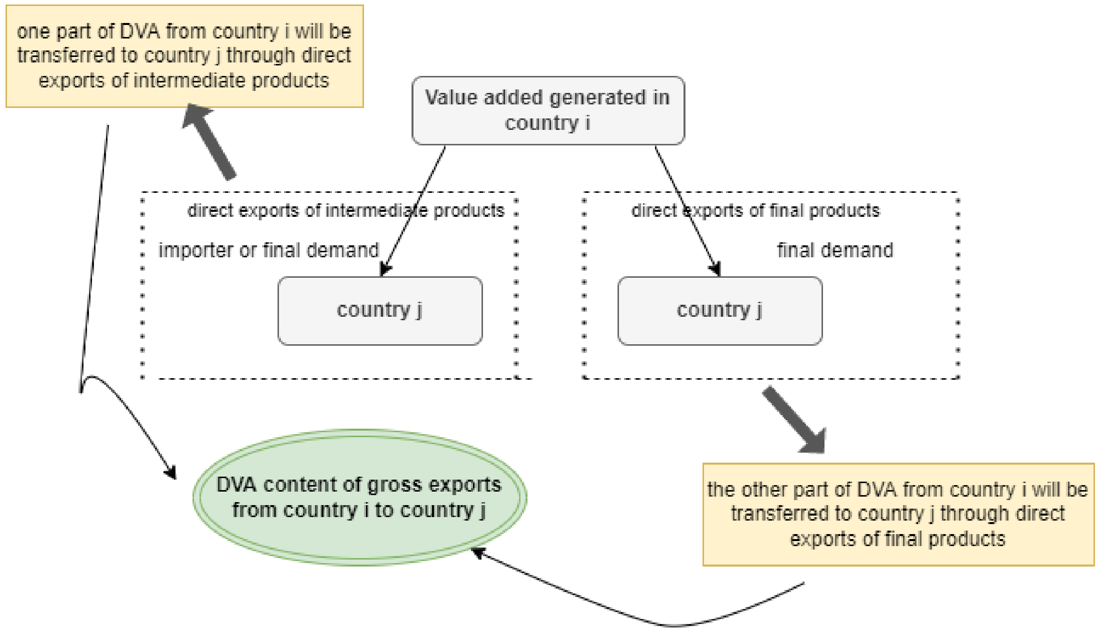


Figure B.3: DVA content of gross exports

Source: Own work based on the instructions of OECD TiVA database

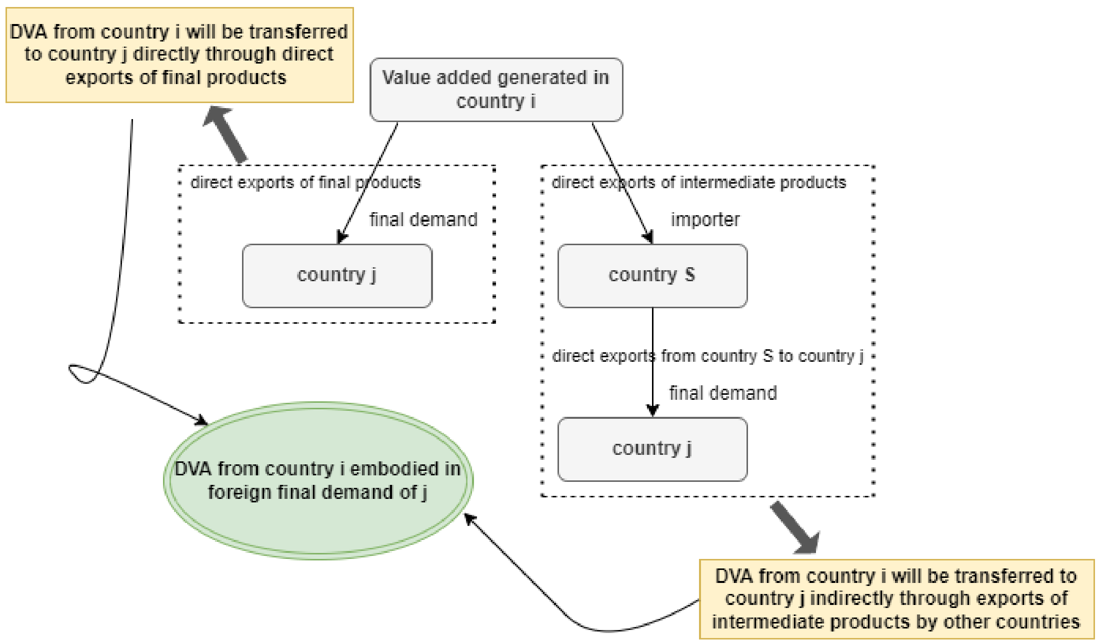


Figure B.4: DVA embodied in foreign final demand

Source: Own work based on the instructions of OECD TiVA database

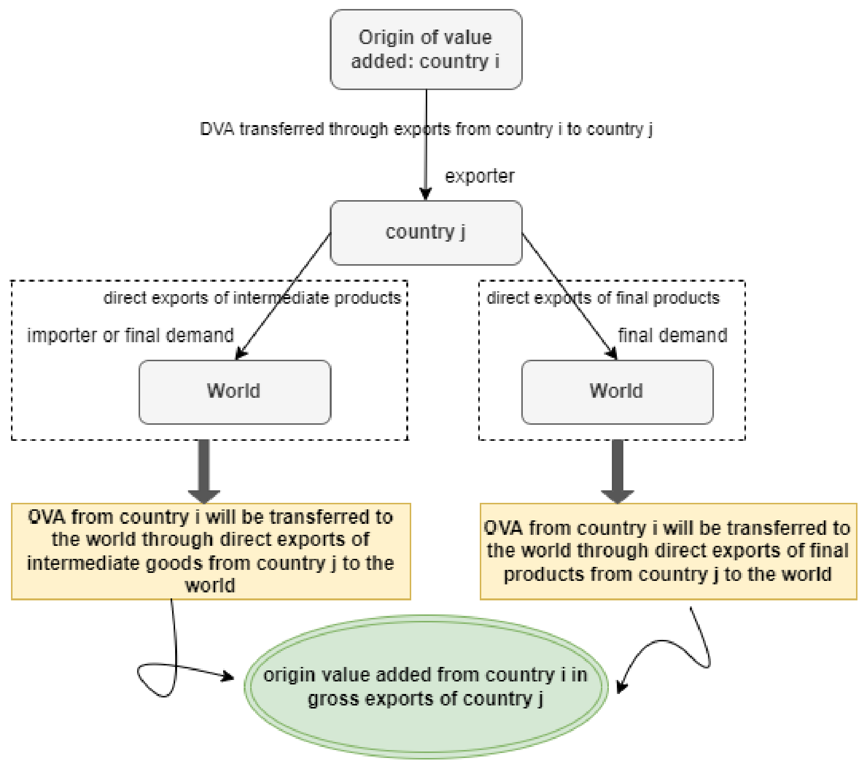


Figure B.5: OVA in gross exports

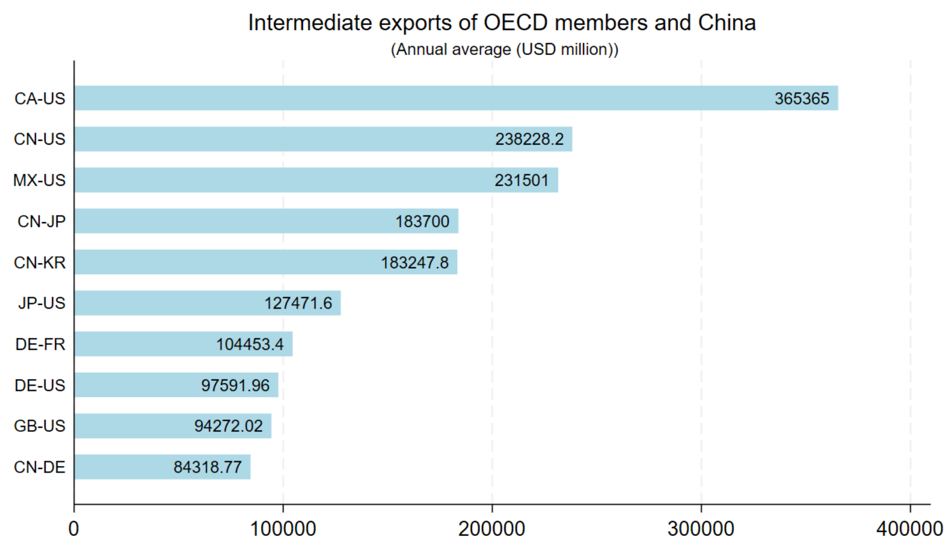
Source: Own work based on the instructions of OECD TiVA database

B.2 Stylised facts of OECD and China

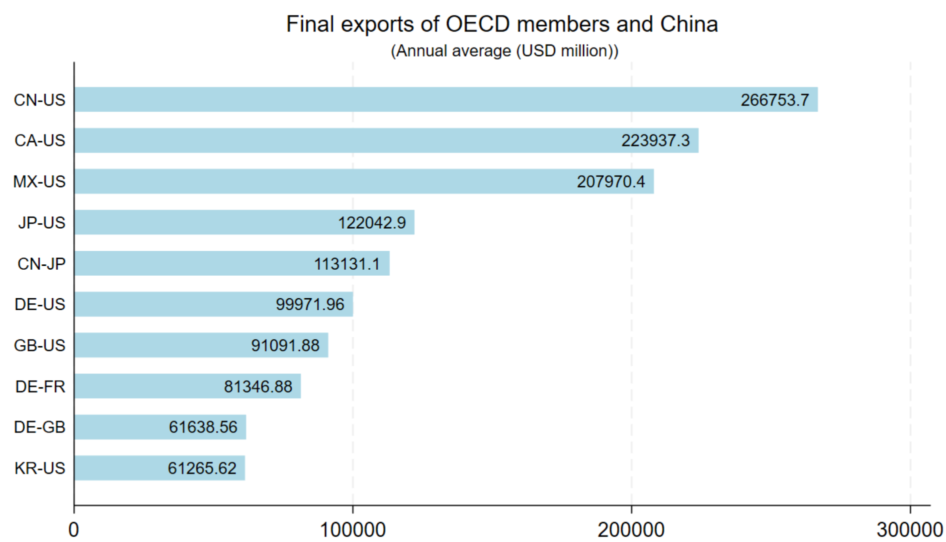
B.2.1 Trade

Figure B.6: The rank of exports in intermediate products, exports in final products and total bilateral exports for OECD members and their largest trade partners

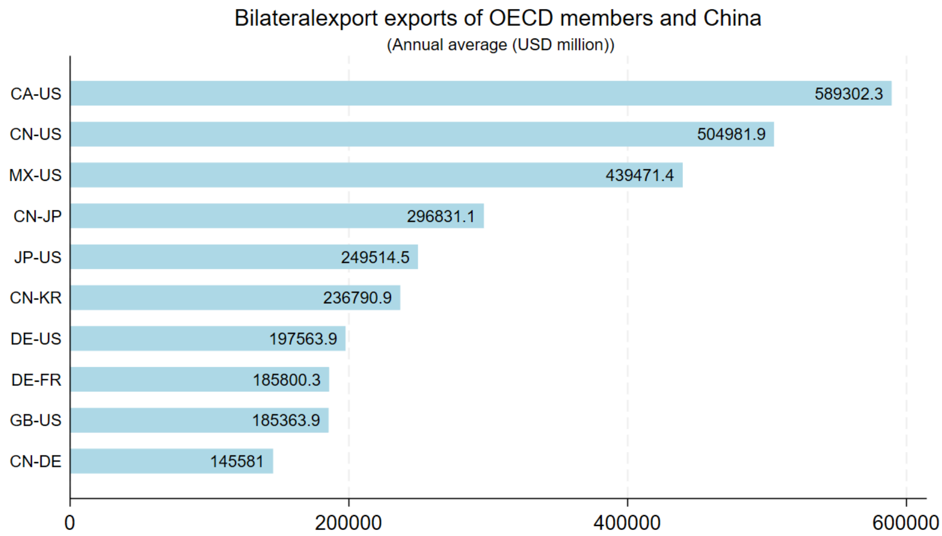
(a) Exports in intermediate products



(b) Exports in Final products



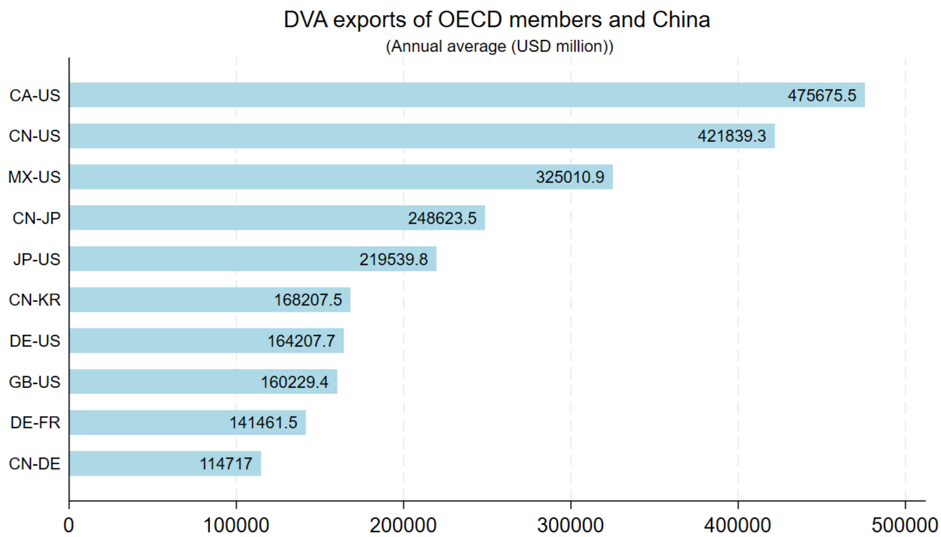
(a) Total Bilateral exports



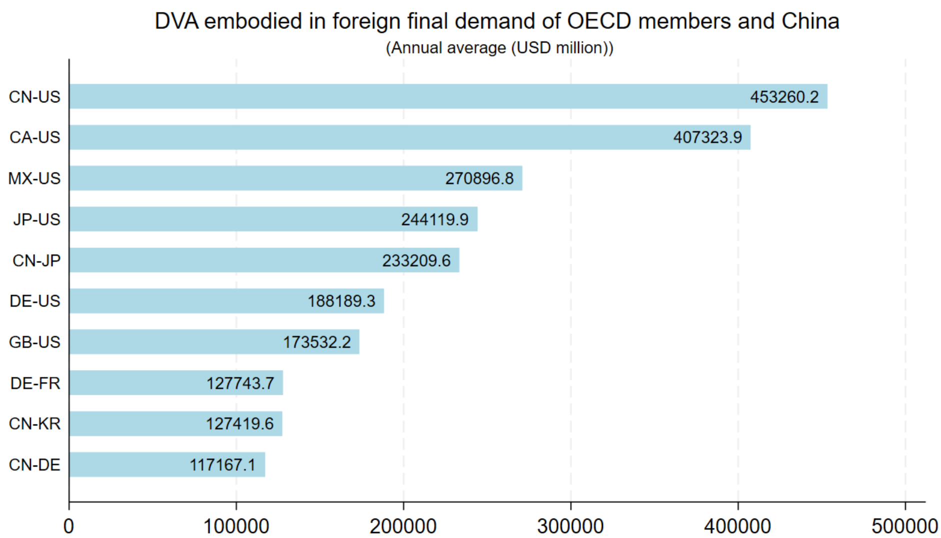
Source: Own calculation based on OECD TiVA database.

Figure B.7: The rank of exports in DVA exports, DVA embodied in foreign final demand and OVA export for OECD members and their largest trade partners

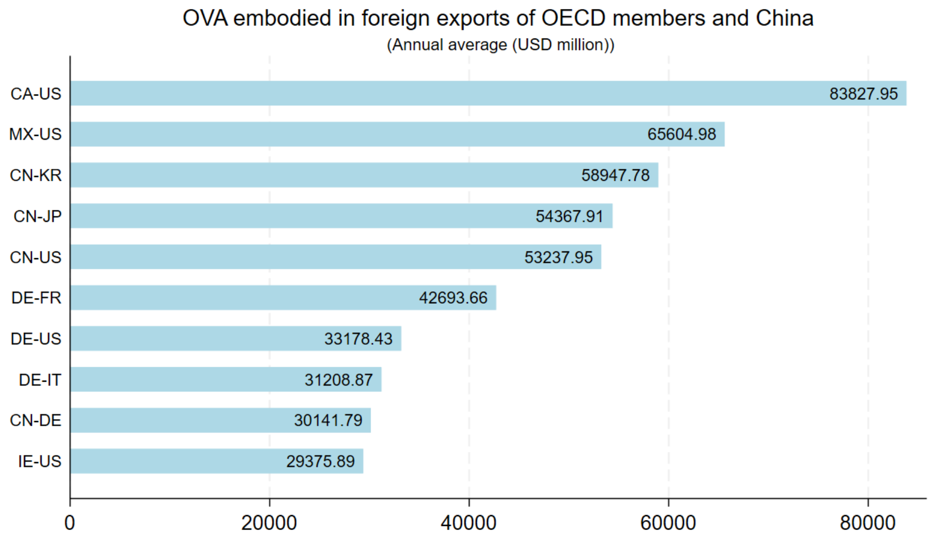
(a) DVA embodied in gross exports



(b) DVA embodied in foreign final demand



(a) OVA embodied in gross exports

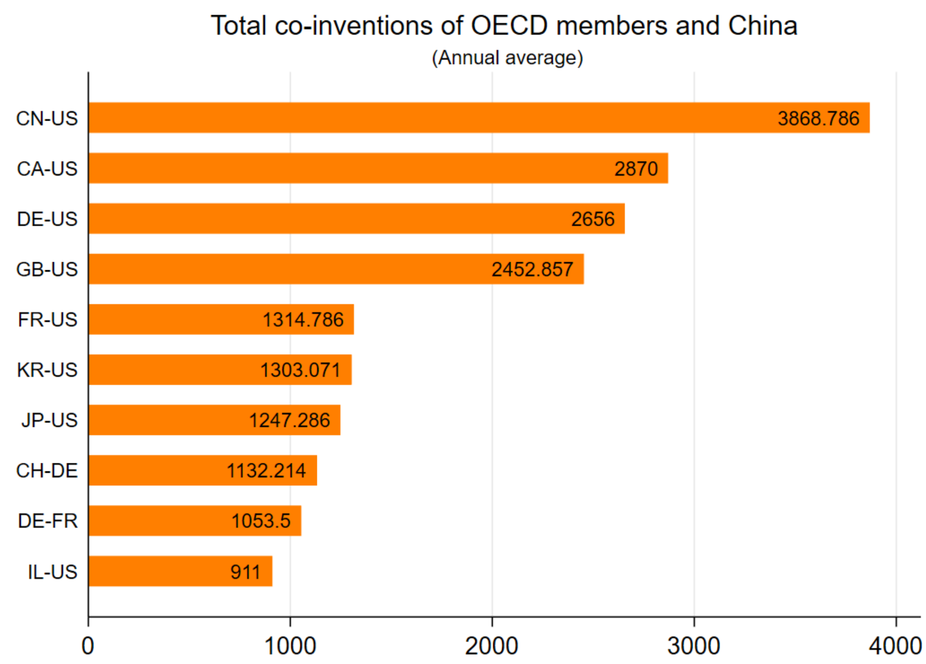


Source: Own calculation based on OECD TiVA database.

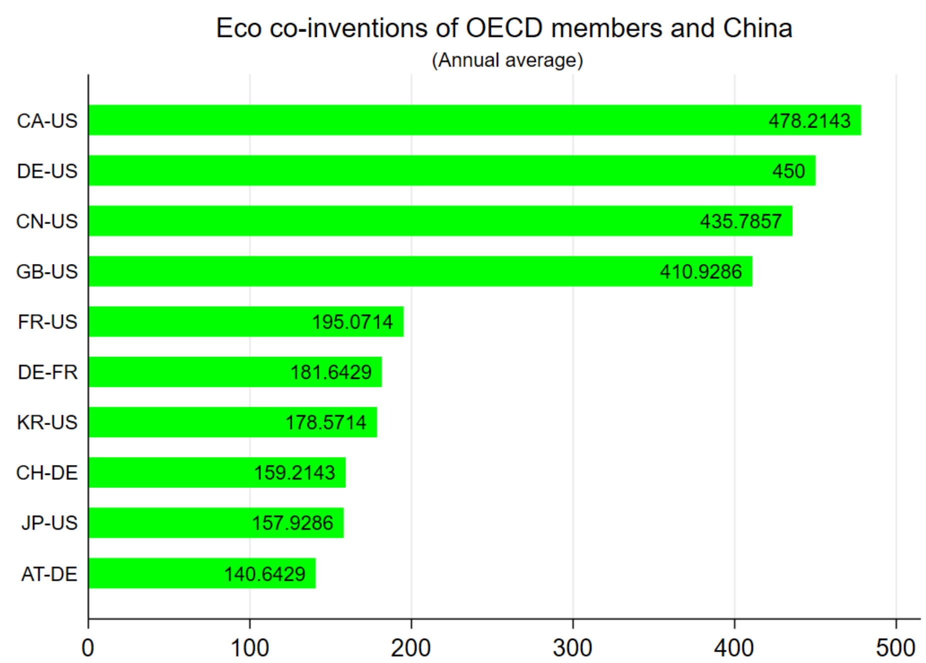
B.2.2 Technological collaboration ranks for OECD and China

Figure B.8: The rank of total collaborative innovation, total collaborative eco-innovation and collaborative non-eco innovation for OECD members and China

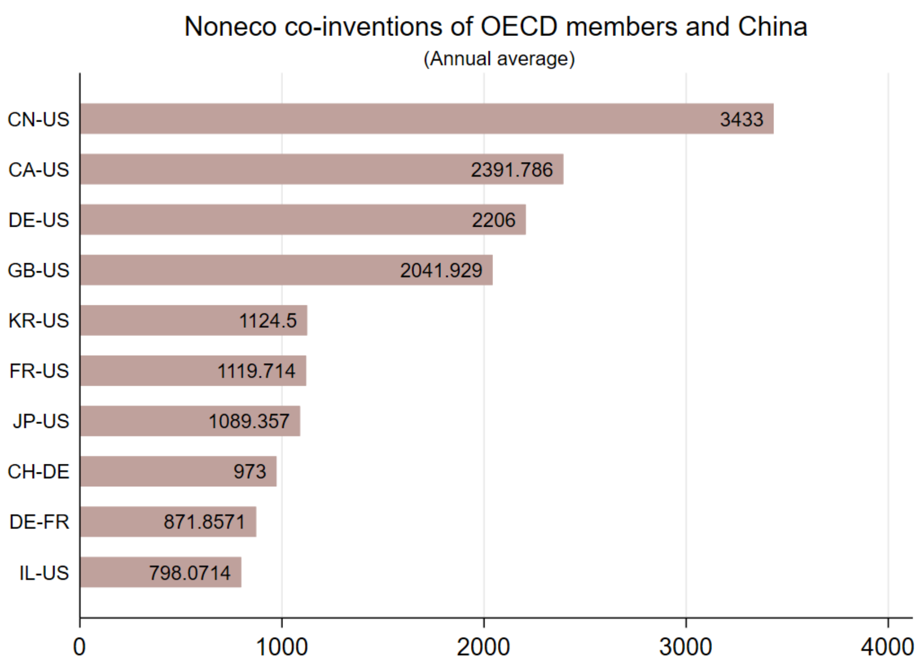
(a) Total collaborative innovation



(b) Total collaborative eco-innovation



(a) Total collaborative non-eco innovation



Source: Own calculation based on PATSTAT database.

B.3 Countries included in our research

Country/Region	**code**
Australia	AU
Austria	AT
Belgium	BE
Canada	CA
Chile	CL
Czech Republic	CZ
Denmark	DK
Estonia	EE
Finland	FI
France	FR
Germany	DE
Greece	GR
Hungary	HU
Iceland	IS
Ireland	IE
Israel	IL
Italy	IT
Japan	JP
Korea	KR
Latvia	LV
Lithuania	LT
Luxembourg	LU

Mexico	MX
Netherlands	NL
New Zealand	NZ
Norway	NO
Poland	PL
Portugal	PT
Slovak Republic	SK
Slovenia	SI
Spain	ES
Sweden	SE
Switzerland	CH
Türkiye	TR
United Kingdom	UK
United States	US
China	CN

B.4 Results of OECD members

Table B.2: Average marginal effects of exports related variables for OECD members (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	7.390***			1.914***			5.815***		
	(1.747)			(0.733)			(1.597)		
log_Final		5.498***			0.965			4.649***	
		(1.856)			(0.745)			(1.712)	
log_Bilateralexport			8.520***			1.830**			6.981***
			(2.000)			(0.831)			(1.829)
Observations	8,274	8,274	8,274	6,963	6,963	6,963	8,218	8,218	8,218
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table B.3: Average marginal effects of value-added related variables for OECD members (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	9.394***			1.912**			7.815***		
	(2.013)			(0.831)			(1.836)		
log_dvaffd		10.847***			1.997*			9.089***	
		(2.690)			(1.117)			(2.434)	
log_ova			8.493***			2.581***			6.519***
			(1.909)			(0.805)			(1.739)
Observations	8,274	8,274	8,274	6,963	6,963	6,963	8,218	8,218	8,218
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table B.4: Average marginal effects of exports related variables for OECD members (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	7.114***			1.650**			5.571***		
	(1.785)			(0.736)			(1.617)		
log_Final		6.148***			1.545**			4.946***	
		(1.889)			(0.776)			(1.721)	
log_Bilateralexport			8.771***			2.010**			7.019***
			(2.028)			(0.842)			(1.842)
Observations	8,288	8,288	8,288	6,979	6,979	6,979	8,246	8,246	8,246
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table B.5: Average marginal effects of value-added related variables for OECD members (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	9.803***			2.020**			8.049***		
	(2.028)			(0.836)			(1.842)		
log_dvaffd		11.923***			2.008*			10.208***	
		(2.711)			(1.145)			(2.439)	
log_ova			9.000***			2.623***			6.805***
			(1.944)			(0.800)			(1.763)
Observations	8,288	8,288	8,288	6,979	6,979	6,979	8,246	8,246	8,246
Country-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
country-pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses

$***$p<0.01, $**$p<0.05, $*$p<0.1

Table B.6: First stage results of IV for OECD members

	1	2	3	4	5	6
VARIABLES	Intermediate	Final	Bilateralexport	dvaexp	dvaffd	ova
log_INS_Intermediate	0.858***					
	(0.005)					
log_INS_Final		0.842***				
		(0.005)				
log_INS_Bilateralexport			0.856***			
			(0.005)			
log_INS_dvaexp				0.850***		
				(0.004)		
log_INS_dvaffd					0.886***	
					(0.004)	
log_INS_ova						0.867***
						(0.005)

	1	2	3	4	5	6
VARIABLES	Intermediate	Final	Bilateralexport	dvaexp	dvaffd	ova
log_TP_i	0.071***	0.061***	0.063***	0.068***	0.045***	0.059***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
log_TP_j	0.082***	0.075***	0.076***	0.081***	0.049***	0.082***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
DIS_ij	-0.111***	-0.093***	-0.099***	-0.105***	-0.061***	-0.111***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
comlangij	0.093***	0.199***	0.128***	0.137***	0.117***	-0.058***
	(0.020)	(0.019)	(0.018)	(0.018)	(0.013)	(0.018)
GVCPi	-0.057***	0.058***	-0.008	0.009	0.038***	-0.056***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.007)	(0.009)
GVCPj	-0.106***	-0.050***	-0.090***	-0.073***	-0.007	-0.148***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.007)	(0.009)
log_GDP_i	-0.016	-0.072***	-0.030**	-0.023*	-0.029***	-0.060***

	1	2	3	4	5	6
VARIABLES	Intermediate	Final	Bilateralexport	dvaexp	dvaffd	ova
	(0.014)	(0.014)	(0.013)	(0.013)	(0.010)	(0.013)
log_GDP_j	0.053***	-0.022*	0.027**	0.039***	0.003	0.023**
	(0.012)	(0.011)	(0.011)	(0.011)	(0.008)	(0.011)
Constant	0.413**	1.924***	0.984***	0.758***	1.053***	1.096***
	(0.189)	(0.178)	(0.174)	(0.170)	(0.128)	(0.168)
Observations	8,820	8,820	8,820	8,820	8,820	8,820
R-squared	0.953	0.956	0.959	0.961	0.976	0.958

Robust z-statistics in parentheses

∗ ∗ ∗p<0.01, ∗∗p<0.05, ∗p<0.1

Table B.7: IV Poisson GMM results of exports related variable for OECD members (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	27.319***			5.584***			22.394***		
	(2.220)			(0.710)			(1.952)		
log_Final		27.811***			5.583***			22.938***	
		(2.179)			(0.809)			(1.926)	
log_Bilateralexport			27.912***			5.631***			22.934***
			(2.200)			(0.740)			(1.942)
log_TP_i	19.978***	19.407***	19.423***	3.359***	3.280***	3.232***	16.690***	16.272***	16.273***
	(1.388)	(1.262)	(1.335)	(0.490)	(0.409)	(0.449)	(1.219)	(1.120)	(1.178)
log_TP_j	16.941***	16.345***	16.326***	2.741***	2.708***	2.656***	14.405***	13.886***	13.900***
	(0.990)	(0.862)	(0.918)	(0.367)	(0.308)	(0.334)	(0.880)	(0.765)	(0.818)
DIS_ij	-3.239**	-4.890***	-3.716***	-0.200	-0.544	-0.291	-2.812**	-4.212***	-3.237***
	(1.281)	(1.019)	(1.156)	(0.360)	(0.353)	(0.345)	(1.133)	(0.903)	(1.025)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	41.553***	39.754***	40.254***	7.016***	6.763***	6.782***	34.685***	33.212***	33.639***
	(2.180)	(2.064)	(2.092)	(0.586)	(0.540)	(0.548)	(1.871)	(1.786)	(1.806)
GVCPi	4.220**	0.408	2.225	1.625**	1.544*	1.509*	2.824	-0.734	1.018
	(1.988)	(1.992)	(1.976)	(0.777)	(0.804)	(0.782)	(1.752)	(1.784)	(1.757)
GVCPj	10.113***	6.695**	8.690***	3.339***	2.609***	3.009***	7.223***	4.536*	6.110**
	(3.040)	(2.964)	(3.011)	(0.799)	(0.698)	(0.749)	(2.645)	(2.586)	(2.621)
log_GDP_i	7.263**	8.028**	6.997**	1.923	1.916	1.889	6.403**	7.342**	6.286**
	(3.472)	(3.641)	(3.498)	(1.173)	(1.205)	(1.179)	(3.043)	(3.207)	(3.072)
log_GDP_j	22.756***	28.322***	24.477***	-0.156	0.719	0.071	21.335***	26.059***	22.804***
	(4.284)	(4.359)	(4.334)	(1.017)	(0.914)	(0.964)	(3.767)	(3.847)	(3.818)
Observations	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table B.8: IV Poisson GMM results of value-added related variable for OECD members (lag1)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	27.553***			5.649***			22.609***		
	(2.156)			(0.707)			(1.899)		
log_dvaffd		29.016***			6.610***			23.522***	
		(2.358)			(0.795)			(2.037)	
log_ova			24.173***			5.487***			19.616***
			(2.146)			(0.718)			(1.857)
log_TP_i	18.512***	18.045***	21.936***	3.040***	2.741***	3.548***	15.551***	15.290***	18.363***
	(1.272)	(1.275)	(1.383)	(0.431)	(0.425)	(0.470)	(1.125)	(1.126)	(1.212)
log_TP_j	15.998***	15.451***	18.752***	2.568***	2.222***	2.731***	13.643***	13.344***	16.028***
	(0.894)	(0.899)	(1.029)	(0.324)	(0.314)	(0.374)	(0.796)	(0.803)	(0.917)
DIS_ij	-3.677***	-6.266***	-6.951***	-0.230	-0.461	-0.643*	-3.233***	-5.513***	-5.947***
	(1.134)	(1.028)	(1.178)	(0.334)	(0.321)	(0.354)	(1.004)	(0.901)	(1.032)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	38.456***	40.979***	48.257***	6.407***	6.695***	8.123***	32.190***	34.432***	40.316***
	(1.999)	(2.096)	(2.321)	(0.527)	(0.560)	(0.656)	(1.731)	(1.809)	(1.982)
GVCPi	-0.155	-4.140**	6.446***	1.035	0.189	1.993***	-0.946	-4.108**	4.701***
	(1.992)	(1.979)	(1.916)	(0.775)	(0.746)	(0.717)	(1.776)	(1.765)	(1.689)
GVCPj	4.453	1.281	15.085***	2.129***	1.486**	4.572***	2.661	0.174	11.245***
	(2.861)	(2.956)	(3.226)	(0.711)	(0.692)	(0.889)	(2.501)	(2.574)	(2.801)
log_GDP_i	7.724**	7.631**	5.466	1.938*	2.323**	1.479	6.924**	6.793**	4.990
	(3.474)	(3.547)	(3.480)	(1.149)	(1.171)	(1.109)	(3.055)	(3.092)	(3.040)
log_GDP_j	24.829***	29.264***	23.385***	0.212	0.959	0.277	23.048***	26.518***	21.644***
	(4.246)	(4.470)	(4.296)	(0.948)	(0.972)	(1.018)	(3.742)	(3.925)	(3.784)
Observations	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820

Robust z-statistics in parentheses

∗ ∗ ∗$p<0.01$, ∗∗$p<0.05$, ∗$p<0.1$

Table B.9: IV Poisson GMM results of exports related variable for OECD members (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_Intermediate	29.785***			5.708***			24.568***		
	(2.256)			(0.680)			(2.006)		
log_Final		29.352***			5.615***			24.304***	
		(2.267)			(0.836)			(2.002)	
log_Bilateralexport			30.077***			5.721***			24.856***
			(2.250)			(0.724)			(2.002)
log_TP_i	18.291***	17.719***	17.811***	3.088***	3.036***	2.975***	15.187***	14.775***	14.849***
	(1.288)	(1.182)	(1.240)	(0.530)	(0.442)	(0.490)	(1.131)	(1.047)	(1.093)
log_TP_j	15.380***	14.973***	14.880***	2.286***	2.232***	2.194***	13.112***	12.819***	12.736***
	(0.958)	(0.843)	(0.889)	(0.372)	(0.290)	(0.332)	(0.855)	(0.753)	(0.794)
DIS_ij	-1.580	-3.838***	-2.360**	-0.153	-0.511	-0.252	-1.213	-3.179***	-1.920*
	(1.271)	(1.040)	(1.152)	(0.347)	(0.331)	(0.322)	(1.144)	(0.931)	(1.037)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	39.843***	38.130***	38.659***	6.699***	6.516***	6.521***	33.127***	31.743***	32.181***
	(2.122)	(2.055)	(2.048)	(0.586)	(0.524)	(0.541)	(1.824)	(1.779)	(1.771)
GVCPi	3.121	-0.479	1.151	0.919	0.646	0.706	2.200	-1.017	0.479
	(2.018)	(2.017)	(2.001)	(0.722)	(0.734)	(0.720)	(1.807)	(1.826)	(1.802)
GVCPj	9.907***	6.170**	8.441***	3.397***	2.767***	3.145***	6.902***	3.910	5.722**
	(2.927)	(2.945)	(2.929)	(0.764)	(0.649)	(0.701)	(2.578)	(2.580)	(2.576)
log_GDP_i	5.996*	7.084*	5.911*	1.181	1.266	1.198	5.290*	6.310**	5.248*
	(3.366)	(3.617)	(3.412)	(1.400)	(1.400)	(1.397)	(2.944)	(3.195)	(2.996)
log_GDP_j	21.046***	26.477***	22.622***	0.168	0.618	0.143	19.855***	24.501***	21.269***
	(4.145)	(4.453)	(4.266)	(1.128)	(0.954)	(1.032)	(3.674)	(3.937)	(3.781)
Observations	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820

Robust z-statistics in parentheses

∗ ∗ ∗p<0.01, ∗∗p<0.05, ∗p<0.1

Table B.10: IV Poisson GMM results of value-added related variable for OECD members (lag2)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
log_dvaexp	29.554***			5.761***			24.371***		
	(2.210)			(0.695)			(1.962)		
log_dvaffd		31.321***			6.645***			25.601***	
		(2.436)			(0.778)			(2.120)	
log_ova_ij			26.637***			5.225***			21.955***
			(2.108)			(0.636)			(1.859)
log_TP_i	16.921***	16.194***	20.286***	2.807***	2.522***	3.353***	14.132***	13.658***	16.865***
	(1.182)	(1.163)	(1.252)	(0.470)	(0.458)	(0.483)	(1.046)	(1.031)	(1.104)
log_TP_j	14.623***	13.889***	17.225***	2.116***	1.809***	2.438***	12.537***	12.058***	14.696***
	(0.870)	(0.869)	(0.982)	(0.324)	(0.321)	(0.350)	(0.778)	(0.776)	(0.875)
DIS_ij	-2.422**	-4.945***	-5.340***	-0.198	-0.408	-0.713**	-2.007**	-4.251***	-4.353***
	(1.137)	(1.035)	(1.150)	(0.312)	(0.310)	(0.324)	(1.022)	(0.916)	(1.023)

	1	2	3	4	5	6	7	8	9
VARIABLES	Collaborative innovation			Collaborative eco-innovation			Collaborative non-eco innovation		
comlangij	36.890***	39.265***	46.854***	6.163***	6.501***	7.763***	30.751***	32.857***	39.047***
	(1.953)	(2.079)	(2.289)	(0.521)	(0.545)	(0.627)	(1.694)	(1.794)	(1.958)
GVCPi	-1.338	-5.719***	5.486***	0.271	-0.572	1.550**	-1.615	-5.230***	3.998**
	(2.027)	(2.025)	(1.897)	(0.727)	(0.725)	(0.680)	(1.823)	(1.809)	(1.688)
GVCPj	3.957	0.054	14.890***	2.282***	1.574**	4.299***	2.050	-1.066	11.062***
	(2.737)	(2.904)	(3.153)	(0.675)	(0.660)	(0.817)	(2.418)	(2.553)	(2.768)
log_GDP_i	6.562*	6.195*	3.344	1.258	1.476	0.529	5.805**	5.479*	3.216
	(3.357)	(3.510)	(3.356)	(1.350)	(1.346)	(1.265)	(2.953)	(3.072)	(2.951)
log_GDP_j	22.965***	27.876***	21.506***	0.249	0.725	0.583	21.492***	25.516***	20.065***
	(4.125)	(4.563)	(4.148)	(1.019)	(1.011)	(1.072)	(3.659)	(4.022)	(3.685)
Observations	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820	8,820

Robust z-statistics in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Appendix C

Appendix to Chapter Four

C.1 Examples of technologies in each technical field

Human Necessities: This category covers technologies related to the daily necessities of human life such as medicine, agriculture, food, personal items, etc.

Performing Operations and Transportation: This category includes technologies for handling, transportation, packaging, and more.

Chemistry and Metallurgy: This category covers chemistry, metallurgy and related technologies, such as new cathode materials for lithium-ion batteries.

Textiles and Paper technology includes new papermaking technology, specific textile technology, etc.

Innovations in fixed construction include insulating materials such as vacuum insulation panels and self-compacting concrete for the exterior of houses.

Mechanical Engineering, Lighting, Heating, Weapons and Explosives include fixed-point blasting systems, LED lighting systems, and military supplies related to weapons.

Physics-related innovations include data storage system, optical products and computers, etc.

Electrical Engineering includes communication-related electronic equipment, 5G communication systems, upgrades and transformations of power supply systems and other related innovations.

C.2 Examples of green technologies in each gren technical field

Alternative Energy Production: This category covers technologies related to non-fossil fuel energy production, such as solar, wind, hydro, geothermal, biomass, etc.

Transportation: This category includes technologies related to green transportation, such as electric vehicles, hybrid vehicles, fuel cell vehicles, optimization of public transportation systems, etc.

Energy Conservation: The energy conservation category focuses on technologies that improve energy efficiency and reduce energy consumption, such as building energy conservation, industrial energy conservation, and home energy conservation.

Waste Management: This category includes technologies for waste treatment, recycling and reuse, such as waste classification, hazardous substance treatment, wastewater treatment, waste gas treatment, etc.

Agriculture and Forestry: This category deals with green technologies in the field of agriculture and forestry, such as smart agriculture, ecological agriculture, sustainable management of forestry, reducing the use of chemical fertilisers and pesticides, etc.

Administrative (Regulatory) or Design Aspects: This category includes technologies related to environmental policy, regulation, and green product design and life cycle assessment.

Nuclear Power Generation: Despite its environmental controversies, nuclear power is still considered a low-carbon energy source. This category includes technologies related to nuclear power generation, such as nuclear reactor design, the nuclear fuel cycle, radiation safety, and more.

C.3 Descriptive Statistics

Table C.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
earliest appln year	2210718	2008.189	4.724	2000	2016
earliest publn year	2210718	2010.007	4.659	2001	2017
time span	2210718	460.231	288.036	53	3000
Collaborative innovation	2210718	0.083	0.275	0	1
Eco-innovation	2210718	0.161	0.367	0	1
forward citations (remove inv)	2210718	8.18	13.205	0	221
forward citations (remove inv & app)	2210718	7.656	12.476	0	221
forward citations (remove examiner)	2210718	5.807	10.834	0	199
backward citation	2210718	9.655	22.655	0	350
family size	2210718	2.28	2.391	1	472
patent scope	2210718	4.613	4.052	1	264
number of inventors	2210718	4.98	6.593	1	358
forward citation index (remove inv)	2210718	0.039	0.062	0	1
forward citation index (remove inv and app)	2210718	0.037	0.059	0	1
forward citation index (remove examiner)	2210718	0.031	0.056	0	1
backward citation index	2210718	0.029	0.069	0	1
CCI (remove inv) index	1593668	0.357	0.295	0	0.938
CCI (remove inv & app) index	1567602	0.355	0.296	0	0.938
CCI (remove examiner) index	1401677	0.323	0.295	0	0.939
family size index	2210718	0.03	0.033	0.002	1

patent scope index	2210718	0.057	0.056	0.004	1
number of inventors index	2210718	0.03	0.04	0.003	1

C.4 Rank

Table C.2: The rank of inventors' residence of countries (regions) (Eco-innovation)

Inventor country	Frequency
United States	63.88%
Japan	13.55%
Republic of Korea	6.02%
Taiwan, Province of China	4.59%
Germany	3.53%
Canada	2.78%
India	2.14%
China	2.34%
United Kingdom	1.74%
Netherlands	1.31%
France	1.15%
Israel	1.00%
Australia	0.62%
Switzerland	0.47%
Italy	0.40%
Singapore	0.39%
Denmark	0.38%
Belgium	0.31%
Sweden	0.28%
Ireland	0.25%

Spain	0.24%
Finland	0.24%
Russia Federation	0.24%
Austria	0.23%
Saudi Arabia	0.22%
Malaysia	0.19%
Brazil	0.17%
New Zealand	0.15%
Mexico	0.10%
Norway	0.08%
Czechia	0.07%
South Africa	0.07%
Thailand	0.06%
Poland	0.06%
Argentina	0.06%
Philippines	0.05%
Turkey	0.05%
Islamic Republic of Iran	0.05%
Ukraine	0.05%
Romania	0.05%
Greece	0.05%
Hungary	0.05%
Costa Rica	0.04%
United Arab Emirates	0.04%

Egypt	0.03%
Chile	0.03%
Bulgaria	0.03%
Indonesia	0.03%
Colombia	0.03%
Kuwait	0.03%

Source: Author's own calculations based on PATSTAT data.

Table C.3: The distribution of inventors' residence of countries (regions) (international collaborative innovation)

Inventor country	Frequency
United States	79.91%
China	18.55%
India	13.67%
Canada	11.97%
Germany	11.59%
United Kingdom	10.72%
Taiwan, Province of China	8.16%
Japan	7.71%
Republic of Korea	6.57%
France	5.95%
Israel	4.20%
Netherlands	3.76%
Switzerland	3.75%
Australia	2.38%
Singapore	2.36%
Italy	2.32%
Belgium	2.19%
Sweden	1.90%
Russia Federation	1.89%
Ireland	1.71%
Austria	1.33%

Finland	1.26%
Spain	1.25%
Malaysia	1.09%
Denmark	1.01%
Brazil	0.75%
Mexico	0.75%
Norway	0.55%
Turkey	0.54%
Czechia	0.50%
New Zealand	0.49%
Poland	0.45%
Romania	0.43%
Saudi Arabia	0.42%
Ukraine	0.38%
Thailand	0.37%
Greece	0.36%
Hungary	0.33%
Philippines	0.31%
Egypt	0.30%
Islamic Republic of Iran	0.28%
Argentina	0.28%
South Africa	0.26%
Pakistan	0.22%
Indonesia	0.21%

Luxembourg	0.20%
Bulgaria	0.20%
United Arab Emirates	0.18%
Vietnam	0.17%
Portugal	0.17%

Source: Author's own calculations based on PATSTAT data.

Table C.4: Distribution of forward citations by country of inventor, for eco-innovation.

Inventor country	Frequency
United States	49.85%
Japan	13.88%
Republic of Korea	7.72%
Germany	7.11%
China	5.46%
Taiwan, Province of China	4.04%
United Kingdom	3.00%
Canada	2.76%
France	2.51%
India	2.03%
Israel	1.26%
Netherlands	1.24%
Italy	0.86%
Switzerland	0.84%
Sweden	0.79%
Australia	0.75%
Finland	0.56%
Belgium	0.53%
Austria	0.53%
Singapore	0.49%
Spain	0.49%
Russia Federation	0.44%

Denmark	0.43%
Ireland	0.34%
Norway	0.22%
Malaysia	0.18%
Brazil	0.18%
Saudi Arabia	0.18%
New Zealand	0.13%
Poland	0.12%
Czechia	0.12%
Mexico	0.11%
Turkey	0.10%
South Africa	0.09%
Hungary	0.08%
Romania	0.06%
Portugal	0.05%
Ukraine	0.05%
Greece	0.05%
Philippines	0.05%
Argentina	0.05%
United Arab Emirates	0.04%
Thailand	0.04%
Bulgaria	0.04%
Chile	0.03%
Luxembourg	0.03%

Islamic Republic of Iran	0.03%
Egypt	0.03%
Colombia	0.02%
Slovakia	0.02%

Source: Author's own calculations based on PATSTAT data.

Table C.5: Distribution of forward citations by country of inventor, for international collaborative innovation.

Inventor country	Frequency
United States	52.67%
Japan	10.54%
Republic of Korea	7.57%
China	7.32%
Germany	6.22%
Taiwan, Province of China	4.68%
United Kingdom	3.54%
Canada	3.14%
India	2.69%
France	2.60%
Israel	1.80%
Netherlands	1.37%
Sweden	1.28%
Switzerland	1.06%
Italy	0.89%
Finland	0.89%
Australia	0.71%
Belgium	0.67%
Singapore	0.59%
Austria	0.50%
Russia Federation	0.48%

Spain	0.45%
Denmark	0.43%
Ireland	0.42%
Norway	0.25%
Malaysia	0.20%
Brazil	0.18%
Poland	0.14%
Saudi Arabia	0.14%
Czechia	0.14%
Turkey	0.12%
New Zealand	0.12%
Mexico	0.11%
Hungary	0.10%
South Africa	0.07%
Greece	0.07%
Romania	0.07%
Ukraine	0.05%
Thailand	0.05%
Argentina	0.05%
Portugal	0.05%
Bulgaria	0.05%
Philippines	0.04%
Luxembourg	0.04%
Egypt	0.04%

Islamic Republic of Iran	0.04%
United Arab Emirates	0.04%
Indonesia	0.03%
Slovakia	0.02%
Vietnam	0.02%

Source: Author's own calculations based on PATSTAT data.

C.5 Other results

Table C.6: Forward citations (only for eco-innovation) (Remove inventor self-citations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Total	Total	AG	AL	EN	TR	NU	WA	AD
CO		0.028***	-0.022	0.013	0.043***	0.043	0.097*	0.048**	0.013
		(0.009)	(0.040)	(0.016)	(0.016)	(0.036)	(0.054)	(0.024)	(0.015)
backward_citation	1.708***	1.708***	1.335***	1.771***	1.828***	1.204***	1.343***	1.456***	1.650***
	(0.022)	(0.022)	(0.080)	(0.049)	(0.050)	(0.064)	(0.102)	(0.056)	(0.038)
log_timespan	-0.156***	-0.156***	-0.125***	-0.252***	-0.147***	-0.169***	-0.159***	-0.113***	-0.128***
	(0.005)	(0.005)	(0.027)	(0.010)	(0.011)	(0.019)	(0.035)	(0.015)	(0.008)
log_patent_scope	0.347***	0.347***	0.306***	0.384***	0.288***	0.275***	0.290***	0.310***	0.360***
	(0.004)	(0.004)	(0.023)	(0.008)	(0.008)	(0.014)	(0.032)	(0.012)	(0.007)
log_family_size	0.104***	0.104***	0.181***	0.195***	0.203***	0.149***	0.220***	0.118***	0.198***
	(0.004)	(0.004)	(0.026)	(0.011)	(0.011)	(0.020)	(0.034)	(0.015)	(0.009)
log_number_of_inventors	0.110***	0.108***	0.054**	0.105***	0.072***	0.084***	0.016	0.087***	0.035***
	(0.003)	(0.003)	(0.024)	(0.008)	(0.008)	(0.014)	(0.022)	(0.012)	(0.006)
US	0.286***	0.283***	0.138***	0.169***	0.282***	0.230***	0.142***	0.139***	0.472***
	(0.005)	(0.005)	(0.034)	(0.010)	(0.010)	(0.018)	(0.032)	(0.018)	(0.011)
Constant	-0.808***	-0.815***	-0.925***	0.021	-0.949***	-0.800***	-0.772***	-1.035***	-0.811***
	(0.033)	(0.033)	(0.199)	(0.070)	(0.068)	(0.122)	(0.226)	(0.104)	(0.054)
Observations	355,769	355,769	9,989	102,304	96,026	29,351	7,178	29,535	115,838
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C.7: International knowledge spillovers (only for eco-innovation) (Remove inventor self-citations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Total	Total	AG	AL	EN	TR	NU	WA	AD
CO		0.069***	0.057**	0.065***	0.075***	0.068***	0.109***	0.102***	0.060***
		(0.005)	(0.029)	(0.009)	(0.008)	(0.016)	(0.037)	(0.017)	(0.008)
backward_citation	0.663***	0.663***	0.615***	0.652***	0.677***	0.432***	0.611***	0.562***	0.604***
	(0.012)	(0.012)	(0.056)	(0.026)	(0.023)	(0.036)	(0.061)	(0.040)	(0.019)
log_timespan	-0.056***	-0.057***	-0.077***	-0.082***	-0.070***	-0.060***	-0.089***	-0.062***	-0.041***
	(0.003)	(0.003)	(0.024)	(0.007)	(0.006)	(0.010)	(0.026)	(0.013)	(0.005)
log_patent_scope	0.129***	0.129***	0.143***	0.089***	0.094***	0.094***	0.149***	0.130***	0.188***
	(0.002)	(0.002)	(0.019)	(0.006)	(0.005)	(0.008)	(0.024)	(0.011)	(0.004)
log_number_of_patents	0.036***	0.036***	0.076***	0.093***	0.062***	0.062***	0.062**	0.040***	0.043***
	(0.003)	(0.003)	(0.021)	(0.007)	(0.006)	(0.010)	(0.025)	(0.013)	(0.005)
log_number_of_inventors	0.030***	0.024***	0.033*	0.007	0.013***	-0.001	-0.011	0.037***	0.014***
	(0.002)	(0.002)	(0.017)	(0.005)	(0.004)	(0.007)	(0.018)	(0.010)	(0.004)
US	0.149***	0.141***	0.055*	0.090***	0.149***	0.152***	0.147***	0.116***	0.200***
	(0.003)	(0.003)	(0.030)	(0.007)	(0.005)	(0.010)	(0.027)	(0.015)	(0.007)
Constant	-0.147***	-0.163***	-0.028	0.035	-0.099***	-0.219***	-0.214	-0.244***	-0.096***
	(0.020)	(0.020)	(0.175)	(0.046)	(0.036)	(0.066)	(0.171)	(0.088)	(0.032)
Observations	249,434	249,434	5,836	62,478	77,847	23,642	5,114	19,570	82,751
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.8: Forward citations (only for eco-innovation) (Remove inventor & applicants self-citations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Total	Total	AG	AL	EN	TR	NU	WA	AD
CO		0.030***	-0.044	0.007	0.051***	0.059	0.080	0.052**	0.011
		(0.009)	(0.042)	(0.017)	(0.017)	(0.036)	(0.056)	(0.024)	(0.015)
backward_citation	1.614***	1.613***	1.266***	1.638***	1.687***	1.095***	1.324***	1.397***	1.581***
	(0.022)	(0.022)	(0.083)	(0.051)	(0.051)	(0.066)	(0.103)	(0.055)	(0.038)
log_timespan	-0.167***	-0.167***	-0.129***	-0.298***	-0.158***	-0.173***	-0.161***	-0.113***	-0.132***
	(0.005)	(0.005)	(0.027)	(0.011)	(0.011)	(0.020)	(0.035)	(0.015)	(0.008)
log_patent_scope	0.342***	0.342***	0.322***	0.365***	0.284***	0.265***	0.303***	0.305***	0.357***
	(0.004)	(0.004)	(0.024)	(0.008)	(0.009)	(0.014)	(0.032)	(0.012)	(0.007)
log_family_size	0.115***	0.115***	0.168***	0.234***	0.205***	0.162***	0.228***	0.124***	0.209***
	(0.004)	(0.004)	(0.027)	(0.012)	(0.011)	(0.021)	(0.035)	(0.015)	(0.009)
log_number_of_inventors	0.110***	0.108***	0.055**	0.123***	0.072***	0.076***	0.013	0.080***	0.027***
	(0.003)	(0.003)	(0.025)	(0.008)	(0.008)	(0.014)	(0.023)	(0.012)	(0.006)
US	0.282***	0.279***	0.144***	0.149***	0.281***	0.235***	0.191***	0.148***	0.469***
	(0.005)	(0.006)	(0.035)	(0.011)	(0.010)	(0.018)	(0.032)	(0.018)	(0.011)
Constant	-0.744***	-0.751***	-0.934***	0.415***	-0.924***	-0.827***	-0.800***	-1.040***	-0.807***
	(0.033)	(0.033)	(0.203)	(0.072)	(0.069)	(0.124)	(0.223)	(0.105)	(0.055)
Observations	355,769	355,769	9,989	102,304	96,026	29,351	7,178	29,535	115,838
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.9: International knowledge spillovers (only for eco-innovation) (Remove inventor & applicants self-citations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Total	Total	AG	AL	EN	TR	NU	WA	AD
CO		0.057***	0.031	0.057***	0.062***	0.057***	0.080**	0.081***	0.051***
		(0.005)	(0.030)	(0.009)	(0.008)	(0.017)	(0.038)	(0.018)	(0.008)
backward_citation	0.664***	0.664***	0.583***	0.665***	0.697***	0.427***	0.595***	0.554***	0.596***
	(0.012)	(0.012)	(0.058)	(0.026)	(0.023)	(0.036)	(0.063)	(0.040)	(0.020)
log_timespan	-0.059***	-0.060***	-0.089***	-0.076***	-0.076***	-0.061***	-0.099***	-0.062***	-0.045***
	(0.003)	(0.003)	(0.024)	(0.007)	(0.006)	(0.011)	(0.027)	(0.013)	(0.005)
log_patent_scope	0.133***	0.133***	0.142***	0.101***	0.096***	0.092***	0.159***	0.131***	0.190***
	(0.003)	(0.003)	(0.020)	(0.006)	(0.005)	(0.008)	(0.024)	(0.011)	(0.004)
log_number_of_patents	0.035***	0.035***	0.077***	0.080***	0.064***	0.063***	0.056**	0.040***	0.048***
	(0.003)	(0.003)	(0.021)	(0.007)	(0.006)	(0.010)	(0.026)	(0.013)	(0.005)
log_number_of_inventors	0.028***	0.023***	0.034**	-0.000	0.016***	0.002	-0.006	0.037***	0.013***
	(0.002)	(0.002)	(0.017)	(0.005)	(0.004)	(0.007)	(0.019)	(0.010)	(0.004)
US	0.140***	0.133***	0.059*	0.088***	0.138***	0.137***	0.129***	0.101***	0.194***
	(0.003)	(0.004)	(0.031)	(0.007)	(0.006)	(0.010)	(0.027)	(0.015)	(0.007)
Constant	-0.126***	-0.139***	0.037	-0.034	-0.040	-0.195***	-0.123	-0.230***	-0.056*
	(0.020)	(0.020)	(0.177)	(0.047)	(0.036)	(0.067)	(0.173)	(0.089)	(0.033)
Observations	245,474	245,474	5,732	60,890	76,923	23,335	5,011	19,317	81,821
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.10: Forward citations (only for eco-innovation) (Remove examiner citations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Total	Total	AG	AL	EN	TR	NU	WA	AD
CO		0.027***	-0.045	0.005	0.053***	0.067	0.118*	0.048*	0.009
		(0.010)	(0.048)	(0.019)	(0.020)	(0.045)	(0.065)	(0.028)	(0.017)
backward_citation	1.720***	1.720***	1.424***	1.865***	1.923***	1.252***	1.508***	1.528***	1.643***
	(0.024)	(0.024)	(0.088)	(0.056)	(0.056)	(0.071)	(0.112)	(0.060)	(0.040)
log_timespan	-0.163***	-0.164***	-0.187***	-0.304***	-0.153***	-0.161***	-0.182***	-0.117***	-0.119***
	(0.006)	(0.006)	(0.032)	(0.012)	(0.013)	(0.024)	(0.040)	(0.017)	(0.009)
log_patent_scope	0.314***	0.314***	0.324***	0.336***	0.271***	0.241***	0.261***	0.250***	0.323***
	(0.004)	(0.004)	(0.027)	(0.009)	(0.010)	(0.017)	(0.037)	(0.014)	(0.008)
log_family_size	0.086***	0.086***	0.135***	0.192***	0.143***	0.094***	0.211***	0.092***	0.191***
	(0.005)	(0.005)	(0.030)	(0.013)	(0.013)	(0.025)	(0.041)	(0.018)	(0.010)
log_number_of_inventors	0.107***	0.105***	0.085***	0.126***	0.073***	0.090***	-0.023	0.096***	0.020***
	(0.004)	(0.004)	(0.028)	(0.009)	(0.009)	(0.017)	(0.027)	(0.014)	(0.007)
US	0.400***	0.397***	0.254***	0.262***	0.391***	0.320***	0.251***	0.269***	0.596***
	(0.007)	(0.007)	(0.042)	(0.012)	(0.012)	(0.023)	(0.039)	(0.022)	(0.013)
Constant	-1.128***	-1.135***	-0.834***	0.044	-1.399***	-1.265***	-1.021***	-1.371***	-1.243***
	(0.038)	(0.038)	(0.240)	(0.083)	(0.082)	(0.149)	(0.260)	(0.122)	(0.060)
Observations	355,764	355,764	9,989	102,304	96,026	29,351	7,178	29,535	115,838
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.11: International knowledge spillovers (only for eco-innovation) (Remove examiner citations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Total	Total	AG	AL	EN	TR	NU	WA	AD
CO		0.057***	0.021	0.066***	0.061***	0.068***	0.063	0.095***	0.049***
		(0.006)	(0.033)	(0.011)	(0.009)	(0.021)	(0.043)	(0.021)	(0.010)
backward_citation	0.686***	0.686***	0.630***	0.707***	0.735***	0.467***	0.649***	0.593***	0.605***
	(0.013)	(0.013)	(0.062)	(0.029)	(0.026)	(0.043)	(0.071)	(0.046)	(0.022)
log_timespan	-0.056***	-0.057***	-0.106***	-0.066***	-0.072***	-0.056***	-0.116***	-0.062***	-0.039***
	(0.004)	(0.004)	(0.027)	(0.008)	(0.007)	(0.013)	(0.031)	(0.015)	(0.006)
log_patent_scope	0.124***	0.124***	0.124***	0.089***	0.088***	0.089***	0.133***	0.127***	0.182***
	(0.003)	(0.003)	(0.021)	(0.006)	(0.006)	(0.010)	(0.027)	(0.012)	(0.005)
log_number_of_patents	0.045***	0.045***	0.103***	0.077***	0.066***	0.054***	0.049	0.027*	0.058***
	(0.003)	(0.003)	(0.024)	(0.008)	(0.006)	(0.013)	(0.030)	(0.015)	(0.006)
log_number_of_inventors	0.029***	0.024***	0.050***	-0.001	0.024***	0.021**	0.006	0.052***	0.015***
	(0.002)	(0.002)	(0.019)	(0.005)	(0.005)	(0.009)	(0.021)	(0.011)	(0.004)
US	0.152***	0.146***	0.067**	0.096***	0.147***	0.145***	0.149***	0.114***	0.223***
	(0.004)	(0.004)	(0.034)	(0.008)	(0.006)	(0.012)	(0.031)	(0.018)	(0.008)
Constant	-0.227***	-0.240***	0.146	-0.209***	-0.146***	-0.326***	-0.131	-0.321***	-0.193***
	(0.024)	(0.024)	(0.197)	(0.053)	(0.042)	(0.083)	(0.198)	(0.104)	(0.039)
Observations	217,581	217,581	5,298	54,568	69,526	20,378	4,521	16,859	71,016
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology field dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Applicants sector dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D

Appendix to Chapter Five

D.1 First stage results

Table D.1: First stage results of OECD + China (ECO_i)

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
Total non-eco innovation_i	0.938***	0.987***	0.954***	0.942***	0.936***
	(0.054)	(0.055)	(0.053)	(0.054)	(0.054)
Total non-eco innovation_j	0.001	-0.003	-0.001	0.000	-0.004
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Total non-eco innovation_i_2	-0.018***	-0.021***	-0.019***	-0.018***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total non-eco innovation_j_2	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GDP_capita_i	-5.312***	-5.381***	-5.372***	-5.225***	-5.216***
	(0.352)	(0.348)	(0.346)	(0.351)	(0.351)
GDP_capita_j	-0.069	-0.013	-0.042	-0.064	-0.074

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Table D.1 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.198)	(0.197)	(0.196)	(0.197)	(0.196)
GDP_capita_i_2	0.276***	0.277***	0.277***	0.273***	0.275***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
GDP_capita_j_2	0.002	-0.000	0.001	0.002	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
CO2_intensity_ij	0.074***	0.099***	0.091***	0.071***	0.117***
	(0.015)	(0.016)	(0.016)	(0.012)	(0.015)
Trade_ij	0.019**	0.020**	0.019**	0.029***	0.041***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)
Scale and composition effect i	0.034***	0.108***	0.103***	-0.012*	-0.037***
	(0.005)	(0.009)	(0.010)	(0.007)	(0.009)
Scale and composition effect j	0.001	0.000	-0.002	-0.000	0.004

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Table D.1 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.006)	(0.009)	(0.008)	(0.009)	(0.010)
Constant	24.826***	24.547***	24.734***	24.503***	24.186***
	(1.941)	(1.924)	(1.908)	(1.937)	(1.938)
Observations	18,529	18,529	18,529	18,529	18,529
R-squared	0.986	0.986	0.986	0.986	0.986
F statistics	891.36	892.04	917.93	896.14	849.06
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Countrypair FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table D.2: First stage results of OECD + China (ECO_j)

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
Total non-eco innovation_j	0.910***	0.947***	0.921***	0.908***	0.906***
	(0.055)	(0.054)	(0.054)	(0.055)	(0.055)
Total non-eco innovation_i	-0.006	-0.001	-0.007	-0.006	-0.018
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Total non-eco innovation_j_2	-0.017***	-0.019***	-0.017***	-0.016***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total non-eco innovation_i_2	0.000	0.000	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GDP_capita_i	0.020	0.085	0.038	0.051	0.140
	(0.202)	(0.202)	(0.200)	(0.202)	(0.202)
GDP_capita_j	-5.167***	-5.255***	-5.230***	-5.030***	-4.951***

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Table D.2 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.360)	(0.354)	(0.353)	(0.357)	(0.354)
GDP_capita_i_2	-0.000	-0.002	-0.001	-0.001	-0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
GDP_capita_j_2	0.269***	0.272***	0.270***	0.264***	0.264***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
CO2_intensity_ij	-0.019	-0.010	-0.016	-0.007	-0.028*
	(0.014)	(0.015)	(0.015)	(0.011)	(0.014)
Trade_ij	-0.019**	-0.046***	-0.033***	-0.028***	-0.083***
	(0.007)	(0.009)	(0.008)	(0.009)	(0.013)
Scale and composition effect i	-0.001	0.004	0.002	0.002	0.011
	(0.006)	(0.009)	(0.008)	(0.009)	(0.010)
Scale and composition effect j	0.033***	0.113***	0.107***	-0.010	-0.031***

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Table D.2 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.005)	(0.009)	(0.010)	(0.007)	(0.009)
Constant	24.359***	23.940***	24.336***	23.422***	22.535***
	(1.984)	(1.959)	(1.947)	(1.975)	(1.950)
Observations	18,529	18,529	18,529	18,529	18,529
R-squared	0.985	0.986	0.986	0.985	0.985
F statistics	886.42	873.69	906.99	881.98	868.33
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Countrypair FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table D.3: First stage results of OECD countries (ECO_i)

	1	**2**	**3**	**4**	**5**
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
Total non-eco innovation_i	0.393***	0.443***	0.420***	0.399***	0.398***
	(0.044)	(0.045)	(0.044)	(0.045)	(0.045)
Total non-eco innovation_j	0.011	0.003	0.008	0.011	0.006
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Total non-eco innovation_i_2	0.016***	0.013***	0.014***	0.016***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total non-eco innovation_j_2	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GDP_capita_i	1.763***	1.484***	1.698***	1.719***	1.782***
	(0.322)	(0.318)	(0.317)	(0.319)	(0.316)
GDP_capita_j	-0.027	0.040	0.009	-0.005	0.042

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Table D.3 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.245)	(0.250)	(0.245)	(0.245)	(0.244)
GDP_capita_i_2	-0.059***	-0.049***	-0.057***	-0.057***	-0.057***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
GDP_capita_j_2	0.001	-0.003	-0.001	-0.001	-0.004
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
CO2_intensity_ij	0.051***	0.061***	0.060***	0.049***	0.082***
	(0.014)	(0.015)	(0.015)	(0.011)	(0.013)
Trade_ij	0.013*	0.017**	0.017**	0.021**	0.035***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Scale and composition effect i	0.010*	0.083***	0.032***	-0.001	-0.060***
	(0.005)	(0.008)	(0.005)	(0.006)	(0.008)
Scale and composition effect j	0.002	-0.000	-0.002	-0.000	0.004

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Table D.3 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.006)	(0.008)	(0.007)	(0.008)	(0.009)
Constant	-10.253***	-9.389***	-10.227***	-10.083***	-10.783***
	(2.021)	(2.019)	(2.003)	(2.001)	(1.992)
Observations	17,521	17,521	17,521	17,521	17,521
R-squared	0.989	0.989	0.989	0.989	0.989
F statistics	689.32	691.35	686.19	683.37	669.57
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Countrypair FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table D.4: First stage results of OECD countries (ECO_j)

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
Total non-eco innovation_j	0.359***	0.407***	0.383***	0.360***	0.357***
	(0.045)	(0.045)	(0.044)	(0.045)	(0.044)
Total non-eco innovation_i	-0.013	-0.005	-0.014	-0.013	-0.019
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Total non-eco innovation_j_2	0.018***	0.015***	0.016***	0.018***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total non-eco innovation_i_2	0.001	0.000	0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GDP_capita_i	0.034	0.023	0.036	0.044	0.064
	(0.252)	(0.256)	(0.251)	(0.252)	(0.250)
GDP_capita_j	2.143***	1.791***	2.061***	2.136***	2.187***

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Table D.4 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.333)	(0.325)	(0.327)	(0.330)	(0.328)
GDP_capita_i_2	-0.002	-0.000	-0.002	-0.002	-0.003
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
GDP_capita_j_2	-0.078***	-0.063***	-0.075***	-0.078***	-0.077***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
CO2_intensity_ij	-0.011	-0.024***	-0.017**	-0.015*	-0.032***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.012)
Trade_ij	-0.035***	-0.006	-0.030**	-0.020*	-0.031**
	(0.013)	(0.014)	(0.014)	(0.010)	(0.013)
Scale and composition effect i	-0.001	0.001	0.000	-0.000	0.003
	(0.006)	(0.009)	(0.007)	(0.008)	(0.009)
Scale and composition effect j	0.008	0.087***	0.034***	0.000	-0.054***

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Table D.4 – continued from previous page

	1	2	3	4	5
VARIABLES	**Intermediate**	**Final**	**Total export**	**dvaexp**	**dvaffd**
	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)
Constant	-11.618***	-10.433***	-11.399***	-11.795***	-12.040***
	(2.082)	(2.069)	(2.060)	(2.077)	(2.055)
Observations	17,521	17,521	17,521	17,521	17,521
R-squared	0.988	0.988	0.988	0.988	0.988
F statistics	671.27	656.32	660.57	654.46	662.90
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Countrypair FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

D.2 Validity test of instrumental variables

D.2.1 OECD+China

	Intermediate	Final	Total export	dvaexp	dvaffd
	Underidentification test				
Kleibergen-Paap rk LM statistic	537.917	752.475	576.72	571.697	608.102
Chi-sq(1) P-value	0.000	0.000	0.000	0.000	0.000
	Weak identification test				
Cragg-Donald Wald F statistic)	480.798	494.028	481.43	483.415	487.159
Kleibergen-Paap rk Wald F statistic	152.175	224.279	165.259	165.213	177.305

D.2.2 OECD

	Intermediate	Final	Total export	dvaexp	dvaffd
	Underidentification test				
Kleibergen-Paap rk LM statistic	720.941	777.96	741.035	724.124	727.509
Chi-sq(1) P-value	0.000	0.000	0.000	0.000	0.000
	Weak identification test				
Cragg-Donald Wald F statistic)	512.886	545.731	527.774	518.993	516.503
Kleibergen-Paap rk Wald F statistic	257.677	286.287	269.441	258.09	258.413

(1) The underidentification test evaluates the null hypothesis positing that the model is underidentified, meaning that the chosen instrumental variables are not significantly correlated with the endogenous predictors. A rejection of the null hypothesis via this test statistic substantiates the identifiability of the model and confirms the relevance of the instrumental variables. (2) This statistic is frequently employed to assess the strength of instrumental variables. However, its validity rests on the assumption of homoskedastic errors. In the presence of heteroskedasticity, the Kleibergen-Paap rk Wald F statistic serves as a more robust alternative for assessing instrument strength. (3) Obtaining a Kleibergen-Paap rk Wald F statistic exceeding the threshold of 10 bolsters confidence in the strength of the instrumental variables, reducing concerns related to weak instrument bias.

D.3 Countries included in our research

Country/Region	code
Australia	AU
Austria	AT
Belgium	BE
Canada	CA
Chile	CL
Czech Republic	CZ
Denmark	DK
Estonia	EE
Finland	FI
France	FR
Germany	DE
Greece	GR
Hungary	HU
Iceland	IS
Ireland	IE
Israel	IL
Italy	IT
Japan	JP
Korea	KR
Latvia	LV
Lithuania	LT
Luxembourg	LU

Mexico	MX
Netherlands	NL
New Zealand	NZ
Norway	NO
Poland	PL
Portugal	PT
Slovak Republic	SK
Slovenia	SI
Spain	ES
Sweden	SE
Switzerland	CH
Türkiye	TR
United Kingdom	UK
United States	US
China	CN