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EVALUATION OF TECHNOLOGICAL CAPABILITIES RELATED TO GREEN TECHNOLOGIES IN CHILE

POR
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Resumen

El cambio climático es un desafío mundial urgente que requiere esfuerzos coordinados de los gobiernos para impulsar el desarrollo sostenible. Entre las políticas disponibles, la especialización inteligente ha ganado relevancia para fomentar la innovación verde mediante el aprovechamiento de capacidades nacionales, especialmente en la Unión Europea. Sin embargo, su efectividad en economías emergentes ha sido poco estudiada. Esta tesis analiza los factores que impulsan el desarrollo tecnológico verde a nivel global entre 1976 y 2025. A partir de datos de patentes, se mapean las capacidades tecnológicas de los países, identificando elementos que influyen en la aparición de nuevas tecnologías verdes. Los resultados indican que una mayor relatedness density, que muestra la proximidad entre capacidades existentes, se asocia positivamente al surgimiento de tecnologías verdes. Estas tecnologías, sin embargo, presentan dinámicas más complejas y menos predecibles, al depender de capacidades previas verdes y no verdes, lo que evidencia dependencia del camino. Aunque las economías avanzadas lideran la innovación verde, regiones emergentes como América Latina fortalecen sus capacidades tecnológicas. El caso de Chile refleja una transición progresiva hacia tecnologías verdes, basada en fortalezas existentes. Los hallazgos resaltan la necesidad de estrategias territoriales que impulsen capacidades existentes para una transición verde inclusiva y sostenible.

Abstract

Climate change presents one of the most urgent challenges of our time, requiring coordinated efforts from governments to drive sustainable development. Among the available policy instruments, smart specialization has gained relevance as a strategy to promote green innovation by leveraging regional strengths, particularly in the European Union. However, its effectiveness in emerging economies remains less explored. This thesis investigates the global patterns and drivers of green technological development from 1976 to 2025. Based on patent data, it maps technological capabilities at the country level, identifying factors that influence the emergence of green technologies. The results show that higher levels of relatedness density, reflecting the proximity of existing capabilities, are positively associated with the development of new green technologies. These technologies, however, exhibit more complex and less predictable dynamics, relying on both green and non-green pre-existing capabilities, which points to strong path dependence. While advanced economies dominate global green innovation, emerging regions like Latin America are gradually strengthening their technological capabilities. The case of Chile illustrates a progressive shift toward greener activities by building on existing industrial strengths. The findings underscore the importance of designing place-based innovation strategies that enhance current strengths to support a more inclusive and sustainable green transition.

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1 Introduction

Climate change, driven primarily by anthropogenic greenhouse gas emissions, poses an unprecedented challenge to global ecosystems, economies and societies (Calvin et al., 2023). In response to this growing crisis, the international community has established a series of coordinated frameworks to limit global warming. For example, the United Nations Framework Convention on Climate Change (UNFCCC) has sought to stabilize greenhouse gas concentrations and prevent dangerous interference with the climate system (United Nations, 1992). Building on this commitment, the Paris Agreement, signed in 2015 and ratified by Chile in February 2017, sets the goal of limiting global temperature increases to well below 2°C above pre-industrial levels, with efforts to further constrain the rise to 1.5°C (United Nations, 2015).

Chile has adopted this agenda by committing to a series of nationally determined contribution (NDC) which represent the country's voluntary commitment to reduce greenhouse gas emissions. The most recent update, presented in 2020 and strengthened during the 2022 United Nations Climate Change Conference (COP), sets a national target of not exceeding 1100 million tons of CO_2 equivalent between 2020 and 2030 (Gobierno de Chile, 2020). Chile is also considered highly vulnerable to climate change, meeting seven of the nine UNFCCC vulnerability criteria (Gobierno de Chile, 2022), given that projections from the Atlas de Riesgos Climáticos (ARClim) estimate temperature increases of 1.15°C to 2°C between 2035 and 2065, with anticipated consequences across ecological, economic, and human systems (Ministerio Del Medio Ambiente, 2020).

To address these challenges, Chile has developed an institutional architecture to support, mitigate risks and enhance resilience across multiple sectors and territorial levels. A milestone in this process is the enhancement of the Framework Law on Climate Change (Law 21.455), published in June 2022, which sets the legally binding target of achieving carbon neutrality by 2050. This legislation outlines the architecture for long-term mitigation planning and guides the formulation of instruments such as the Long-Term Climate Strategy, the NDC, and a multilevel system of sectoral, regional, and local action plans. These instruments define the responsibilities of various public institutions and set out sectoral emission budgets to align national development with climate objectives. Complementing this legal framework, the National Climate Change Action Plan 2017–2022 (PANCC) emphasizes technology transfer and innovation. It includes measures to develop a national strategy for climate-relevant technology, promote research centers, and foster climate literacy, international cooperation, and green finance (Gobierno de Chile, 2017).

This institutional and regulatory environment is further reinforced by Chile's capabilities for renewable energy development, rooted in its geography and natural resources. The northern regions receive some of the highest levels of solar radiation globally, ideal for photovoltaic energy. while the coastal and southern zones possess high wind potential (Gobierno de Chile, 2022). Moreover, Chile holds 41% of the world's lithium reserves (Stephany Griffith-Jones et al., 2023) a critical raw material for the development of green technologies. These conditions position Chile not only as a country vulnerable to climate change but also as a territory with exceptional potential to lead in the deployment and export of green tech solutions.

While Chile's climate roadmap reinforces this ambition by setting concrete milestones: by 2030, 80% of electricity should come from renewables and zero-emission fleets should operate in mining; by 2040, 20% of the fuel matrix should derive from green hydrogen and public transport should be fully electric; by 2050, the energy matrix should be carbon neutral and industrial emissions reduced by 70% (Gobierno de Chile, 2022); yet, these targets lack a clear understanding of where real opportunities lie within the country's technological development in green-based technologies. Without structured, country-specific analysis, it remains unclear which sectors can feasibly drive the green transition.

This thesis addresses this gap by evaluating the country's capabilities in the development of green technologies, identifying strategic sectors for diversification using relatedness analysis and Machine Learning. These insights are intended to support evidence-based policy decisions that contribute to climate resilience, sustainable economic development, and the effective implementation of Chile's climate goals.

2 Objectives

2.1 General objective

To evaluate Chile’s technological capabilities in the development of green technologies, with the aim of identifying opportunities for productive diversification and the emergence of future comparative advantages.

2.2 Specific objectives

- Characterize the state-of-the-art in the literature of technological relatedness.
- Analyze diversification opportunities in technologies related to green technologies by applying an econometric model to understand development trajectories.
- Characterize the potential to develop green technologies in Chile, evaluating their interconnection with strategic sectors through models of technological proximity.
- Propose strategic guidelines for the formulation of public policies aligned with Smart Specialization principles aiming at strengthening Chile’s specialization in green technologies and enhancing its international competitiveness.

3 Literature Review

This section provides an overview of the main approaches related to economic complexity and regional diversification. It introduces frameworks that explain how regions develop new capabilities, with attention to the role of knowledge, specialization, and technological change, especially focused on green technologies. This overview also highlights recent perspectives on twin transition and green transition.

3.1 Economic Complexity

Understanding how regions develop technological capabilities begins with a long-standing question in economics: what drives productivity and long-run growth? As early as 1776, Adam Smith emphasized the power of specialization through the division of labor, suggesting that economic progress stems from how individuals and firms organize and refine their productive activities. This intuition would later influence the Solow (1956) growth model, which formalized economic growth as a function of capital accumulation, labor, and an unexplained exogenous force of technological progress. Then, Romer (1994) introduced a perspective that placed knowledge, R&D, and human capital into the heart of growth theory, suggesting that long-run growth results from purposeful human action rather than from external forces. Building upon these models, Hidalgo et al. (2007) argue that economies grow by diversifying the products they produce and export, typically moving into goods related to their existing capabilities, showing that countries embedded in dense areas of *Product Space* can diversify more easily, while those with capabilities on the periphery face greater structural barriers to economic transformation. Hidalgo & Hausmann (2009) extend this perspective by formalizing the term economic complexity as a framework to infer a country's capabilities. They argue that when a country exports two globally relevant goods, these are likely to share underlying capabilities, suggesting that new products emerge from novel combinations of existing endogenous capabilities and more complex economies produce more exclusive goods. Hausmann & Hidalgo (2011) demonstrate that the gains from acquiring new capabilities are disproportionately higher for already diversified countries, reinforcing divergence in product diversity particularly in a global economy where capabilities travel poorly across borders. Balland & Rigby (2017) further show that knowledge complexity is not only unevenly distributed across regions but also varies in its spatial stickiness: while low-complexity knowledge tends to diffuse more easily, complex knowledge is produced in fewer places and proves harder to transfer geographically.

Neffke et al. (2011) find that both entry into and exit from new industries that are technologically related to existing ones are strongly conditioned by the technological coherence of the regional portfolio, highlighting how industrial relatedness drives structural transformation over time. In a similar vein, Boschma (2017) emphasizes the need for conceptual clarity around what relatedness entails, suggesting it may derive from shared knowledge bases, networks, institutions, or skills.

Thus, Hidalgo et al. (2018) formalize the principle of relatedness as the probability that a region will develop new activities based on the presence of related ones, offering a measurable framework grounded in empirical evidence. Relatedness has been widely applied as a lens to examines how cities, regions and countries learn and develop diversification opportunities using different data sets such as international trade data (Boschma et al., 2013; Hausmann & Klinger, 2007; Hidalgo et al., 2007), industry data (Neffke et al., 2011), occupational data (Muneepeerakul et al., 2013), scientific publications (Boschma et al., 2014; Guevara et al., 2016), patent data (Balland et al., 2019; Balland & Boschma, 2021; Kogler et al., 2013; Montresor & Quatraro, 2020; Rigby, 2015) or combined measures like cross-relatedness (Balland & Boschma, 2022; Catalán et al., 2022) who use patent and publication data.

3.2 From Smart Specialization to green transition

Building upon the relatedness literature, Smart Specialization offers a valuable framework to guide the transition toward green technologies. Foray et al. (2009) introduced it as a strategic vision for regional growth rooted in place-based capabilities. Balland et al. (2019) provide a theoretical framework for Smart Specialization grounded in the concepts of relatedness and knowledge complexity, which together helps identify realistic and high-potential diversification opportunities for regions. Moreover, Balland & Boschma (2021) show that the probability of a region developing new technologies also increases when it connects to regions with complementary capabilities. Similarly Boschma et al. (2025) find that participation on global value chains contributes to regional economic complexity by combining external linkages with local capabilities.

This supports the hypothesis that countries with greater productive sophistication are better equipped to undertake green transitions in a competitive and sustainable manner. As shown by Mealy & Teytelboym (2022), countries with higher green complexity export more advanced green products and demonstrate stronger environmental performance, thus contributing to both economic growth and sustainability (Belmartino, 2022). According to Bachtrögler-Unger et al. (2023), over 80% of twin (i.e., digital and green) technologies are concentrated in Europe’s most developed regions, and in the case of green hydrogen, innovation is largely confined to industrialized countries (Müller & Eichhammer, 2023).

Green technologies typically emerge from existing capabilities, including those rooted in polluting sectors, following cumulative path-dependent trajectories (Mealy & Teytelboym, 2022; Perruchas et al., 2020; Santoalha & and Boschma, 2021). As Colombelli & Quatraro (2019) argue, this process is enabled by cognitive proximity and technological variety, alongside key enablers such as R&D investment, skilled professionals, and science-based employment (Bergamini & Zachmann, 2021). Tsouri & Boschma (2024) find that regional entry into photovoltaic technologies relies more on embedded knowledge than on external flows. Moreover, the recombination of green and non-green capabilities, particularly through Key Enabling Technologies (KETs), can help regions overcome lock-in and expand their innovation potential, even in less advanced areas (Montresor & Quatraro, 2020).

In addition to knowledge-based factors, material conditions are also relevant. An increased supply of rare metals such as lithium boosts the patent output of technologies (Li et al., 2024), while domestic production of critical raw materials significantly enhances renewable energy exports and innovation (Li & Iammarino, 2024). This is especially relevant for Chile, whose abundant reserves of lithium, copper, and rare earth elements (Álvarez Calderón & Trujillo Palacio, 2020; Stephany Griffith-Jones et al., 2023), position it strategically to transition toward more complex and innovation-driven green technologies.

Although most empirical evidence comes from advanced economies, a growing body of research is beginning to explore how green diversification unfolds in emerging contexts, particularly in Latin America. Belmartino (2022) finds that green diversification is path-dependent and shaped by relatedness in Argentina, with both green and non-green capabilities contributing. Françoso et al. (2024) show that in Brazil, relatedness drives diversification, but only high-complexity regions transition into more sophisticated activities. Pérez-Hernández et al. (2025) identify country-specific green export opportunities in the Southern Cone, noting underused high-value, low-emission options.

These insights highlight the relevance of extending the Smart Specialization lens to less studied geographies. Despite its strategic potential, the framework remains underutilized in Latin America and virtually absent in Chile, especially when we are interested in understanding the development of green technologies. Considering the theoretical discussion, this study aims to address that gap by incorporating patent data focusing on green technological classifications to map and evaluate the regional knowledge base worldwide, with a focus in Chile. To this end, a classification-based technique is applied to estimate the effect of relatedness on the entry of green technological capabilities. This approach allows to provide a more complete and policy-relevant diagnosis of Chile's diversification potential, offering an evidence-based foundation to adapt Smart Specialization principles to the Chilean context.

4 Data and Methodology

This section describes the data sources, the framework for measuring specialization and relatedness, the green technology classification used, and the estimation model for technological entry.

Previous studies have employed patent data from the United States Patent and Trademark Office (USPTO) to examine the dynamics of technological knowledge evolution in U.S. metropolitan areas, such as Boschma et al. (2015) and Balland & Rigby (2017). Here, a global dataset downloaded from USPTO is used, spanning 1976 to 2025, to examine the development of green technologies and their diffusion. The analysis is conducted at the country level, with a technological classification based on the Cooperative Patent Classification (CPC) system aggregated at the 2-digit class level covering 133 classes.

To ensure robustness, global representativeness, and avoid distortions from outliers, the analysis is restricted to the 58 countries that collectively account for 99.9% of all granted patents worldwide over the observed period. Panel datasets are constructed by aggregating unique patents by country, CPC class and year, that guarantee each patent is counted only once.

4.1 Relatedness between technologies

National opportunities for technological diversification are identified using relatedness density, which quantifies how closely a country's existing technological portfolio is connected to a potential new technology (Hidalgo et al., (2007); Boschma et al., (2015); Balland et al., (2019)). This measure is based on the concept of Revealed Comparative Advantage (RCA), which indicates whether a country is relatively specialized in a particular technology. The RCA for country c in technology i at time t is calculated as:

$$RCA_{i,c,t} = \frac{(X_{i,c,t} / \sum_i X_{i,c,t})}{(\sum_c X_{i,c,t}) / \sum_i \sum_c X_{i,c,t})}$$

Where $X_{i,c,t}$ denotes the number of patents filed by country c in technology i, $\sum_i X_{i,c,t}$ is the total number of patents from country c, $\sum_c X_{i,c,t}$ is the global total of patents in technology i, and $\sum_i \sum_c X_{i,c,t}$ is the global total of all patents, all variables are considered to be time-dependent, with t representing an specific year. An RCA value greater than 1 indicates that the country has a relative advantage in that technology.

Based on RCA values, the relatedness matrix $\phi_{ij,t}$ is constructed to capture the minimum conditional probability that two technologies i and j co-occur with RCA ≥ 1 within the same country at time t:

$$\phi_{i,j,t=}min(P(\ RCA_{i,t}\ |\ RCA_{j,t}\ ), P(\ RCA_{j,t}\ |\ RCA_{i,t}\ ))$$

Then, the specialization matrix $M_{i,c,t}$ represents where a country c has comparative advantages in a given product i, where rows represent countries and columns technology classes for each year t can be defined as follows:

$$M_{i,c,t} = \begin{cases} 1, & if\ RCA_{i,c,t} \geq 1 \\ 0, & Otherwise \end{cases}$$

Following Hidalgo et al. (2007), the relatedness density of each country c in a technology i at time t is computed. The relatedness density is formally defined as:

$$RD_{i,c,t} = \frac{\sum_{j\epsilon c, j\neq i} M_{i,c,t}\ \phi_{i,j,t}}{\sum_{j\neq i} \phi_{i,j,t}} * 100$$

This measure captures how close a potential new technology i is within the current technological structure of a country each year t. The closer technology is, on average, to the existing portfolio of specializations in a country, the higher its relatedness density. Conceptually, it represents the likelihood that a country can successfully diversify into new technology, based on the capabilities it already possesses.

To ensure a robust estimation of technological entry, the analysis incorporates structural and contextual country-year level controls that may influence innovation outcomes beyond technological relatedness. Following Balland et al. (2019) and Boschma et al. (2025), two variables are added: population density as a proxy for agglomeration economies and GDP per capita to account for country's level of economic development. To report for institutional and environmental factors that may shape green technological trajectories, the analysis also considers Foreign Direct Investment (FDI) inflows and average annual exposure to fine particulate matter ($PM_{2.5}$) pollution as Dong et al. (2019) and Dong et al. (2022).

Structural conditions may influence the likelihood that a country develops certain types of technologies over others, particularly those aligned with national needs, financial capacity, and human capital. For instance, countries with higher GDP per capita may have greater resources to invest in R&D, adopt new technologies, or support innovative policies (Dong et al., 2019). Likewise, population density can reflect the size of the skilled workforce or knowledge base available to sustain technological development (Balland et al., 2020; Colombelli & Quatraro, 2019). In addition, the level of investment could shape the feasibility of exploring new technological areas, since they require external resources (Dong et al., 2022). In the case of $PM_{2.5}$, the inclusion is not intended to identify a direct causal effect, but rather to proxy environmental stressors that may increase social and regulatory demand for cleaner technologies (Dong et al., 2022).

4.2 Green and key enable technologies classification

To identify green technologies, the classification developed by Montresor & Quatraro (2020) is followed, which maps specific technological domains to environmental objectives using both the International Patent Classification (IPC) and the CPC systems. As detailed in Tables A1 and A2 of their supplemental material, green technologies and KETs are identified by a list of IPC and CPC codes associated with areas such as air pollution abatement, energy efficiency, renewable energy, and wastewater treatment. While the original classification includes technology codes at various levels of granularity, including 642 technological subclasses, 65 related to green technologies and 89 to KETs, patent data are aggregated at the two-digit CPC level in this analysis. At this aggregated level, the dataset captures a more focused subset of global patent activity, comprising 133 unique technological classes, of which 39 are classified as green and 67 as KET related (see Appendix 1 and Appendix 2 for full classifications).

4.3 Model specification

To study technological entry at the country level, a logistic regression specification is adopted, following Montresor & Quatraro (2020), who use this method to examine the emergence of green technological specializations. The dataset is structured as a panel, where each observation corresponds to a country-technology pair over time (i.e., panel data with country *c*, technology *i*, and year *t*).

The model is specified as follows:

$$\begin{aligned} Prob(M_{i,c,t} = 1) \\ &= \alpha_1 * relatedness\_density_{i,c,t} + \alpha_2 * is\_green_{i,c,t} \\ &+ \alpha_3 * ket\_count\_prev\_year_{c,t-1} + \beta * X_{c,t} + \mu_t + \varepsilon_{i,c,t} \end{aligned}$$

Where the variable $M_{i,c,t}$ is a binary indicator that indicates whether a country c has entered a new technology i, meaning it has acquired a comparative advantage in a technology not previously present in its portfolio within the last three years. $relatedness\_density_{i,c,t}$ measures how closely a technology is connected to other technologies in which the country is already specialized, $is\_green_{i,c,t}$ indicates whether the technology is classified as green or not, $ket\_count\_prev\_year_{c,t-1}$ counts the distinct patents in which the country c has RCA ≥ 1 in year t-1, $X_{c,t}$ are the country-specific control variables for country *c* and year *t*. Year-fixed effects μ_t were included to absorb time-specific changes including global policy shifts and macroeconomic trends. Although inflation is not explicitly controlled for, year-fixed effects help account for common inflationary pressures across countries and years. This approach mitigates but does not fully eliminate potential bias from unobserved price-level variation.

To ensure comparability and facilitate model estimation, continuous independent variables were standardized prior to analysis with mean equal to zero and variance equal to the unit.

To test robustness, an alternative approach is estimated by splitting the dataset into green and non-green technologies and introducing other fixed effects. Specifically, control year-fixed effects, technology-fixed effects, and the interaction between year and CPC class are included. This model captures time-specific and technology-specific unobserved heterogeneity, accounting for structural shifts or shocks that may influence technology entry patterns. The model is defined as follows:

$$\begin{aligned} Prob\left(M_{i,c,t} = 1\right) \\ &= \alpha_1 * relatedness\_density_{i,c,t} + \alpha_2 * ket\_count\_prev\_year_{c,t-1} + \beta * X_{c,t} + \mu_t \\ &+ \delta_i + \theta_{i,t} + \varepsilon_{i,c,t} \end{aligned}$$

Where the variables are defined as previously. δ_i represents CPC class-fixed effects and $\theta_{i,t}$ denotes CPC class-year fixed effects. A complete overview of variable definitions and data sources is presented in Table 4.3.1.

Table 4.3.1: Variable definitions and data sources

Variable	Description	Source
relatedness_density	Relatedness density measuring proximity of technology i to the country's specialized portfolio.	Calculated with ecomplexity (Harvard Growth Lab) on USPTO PatentsView databases (May 19, 2025).
M_t	Binary flag equals to 1 when country *c* first reaches RCA ≥ 1 in technology *i* at year *t* while RCA < 1 in each of the three preceding years (*t-1*, *t-2*, *t-3*); 0 otherwise.	Author's calculation on the USPTO PatentsView databases (May 19, 2025).
gdp_per_capita	Gross domestic product per capita (current USD).	World Bank Data (1960-2023).
is_green	Dummy equal to 1 if technology i is classified as green; 0 otherwise.	Author's calculation from Montresor & Quatraro (2020) Patent classification codes for green technologies on the USPTO PatentsView databases (May 19, 2025).
ket_count_prev_year	Number of unique KET patents (i.e., patents classified as Key Enabling Technologies) filed in country c during year $t - 1$ with RCA>1.	Author's calculation from Montresor & Quatraro (2020) Patent classification codes for the 6 KETS on the USPTO PatentsView databases (May 19, 2025).
population_density	People per square km (at country level, *c*)	World Bank Data (1961-2022).
pm25_ug_m3	Mean annual exposure $PM_{2.5}$ (at country level, *c*).	World Bank Data (1990-2020).
fdi_net_inflows_usd	Net foreign direct investment inflows to country *c* (current USD at country level, *c*).	World Bank Data (1970-2024).

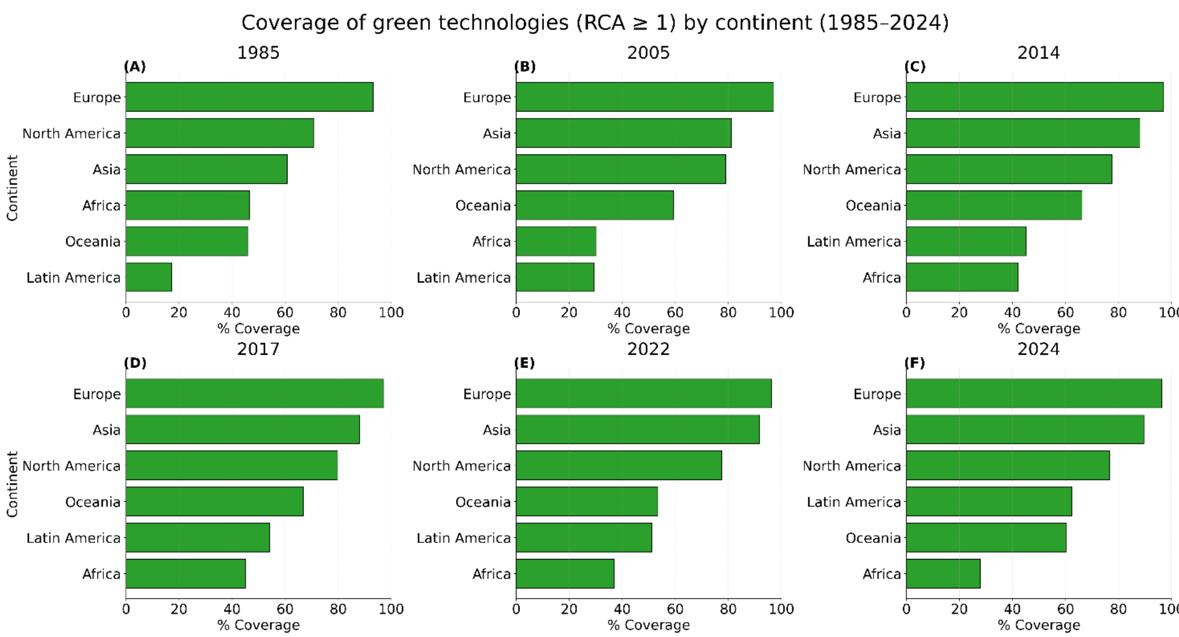
Source: Author's own elaboration.

5 Results

5.1 Geographies and trajectories of green technological capabilities

Over the past three decades, competitive green-tech specializations have both clustered in traditional hubs and diffused across new frontiers. In Figure 5.1.1, Europe emerges as the long-standing epicenter of green innovation, in every snapshot from 1995 to 2024 it leads on green technologies coverage. Its persistently high percentage reflect the cumulative effect of regulatory harmonization and Europe-wide R&D networks that have lowered barriers to cross-border knowledge flows since 1984 European Union (2025), this is further developed in 2010 when smart specialization strategies were implemented focusing on the deployment of innovative activity and the creation of new connections among innovation actors within and beyond the region Foray et al. (2021), leveraging their existing strengths Balland et al. (2019).

Figure 5.1.1: Coverage of green technologies (RCA ≥ 1) by continent (1985-2024)

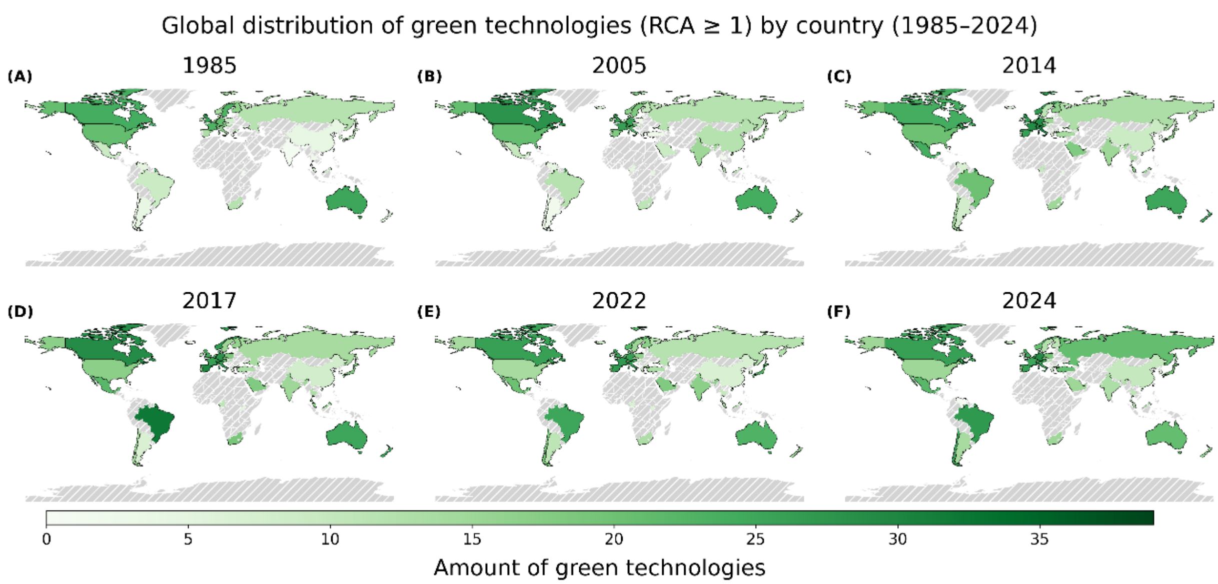


Note: Each panel shows the percentage of unique green CPC classes with revealed comparative advantage in the year indicated for: (A) 1985, (B) 2005, (C) 2014, (D) 2017, (E) 2022, and (F) 2024.

Around 2005, 13 years after the UNFCCC, all continents register a pronounced jump in green coverage, signaling the first wave of global climate-policy impacts. Asia and North America rapidly close the gap, while Oceania, Latin America and Africa emerge from near zero baselines. By 2017–2024, Latin America accelerates most sharply its share rising from ~35 % to over 60 %, which could be consequence of the regional influence of the 2015 Paris Agreement.

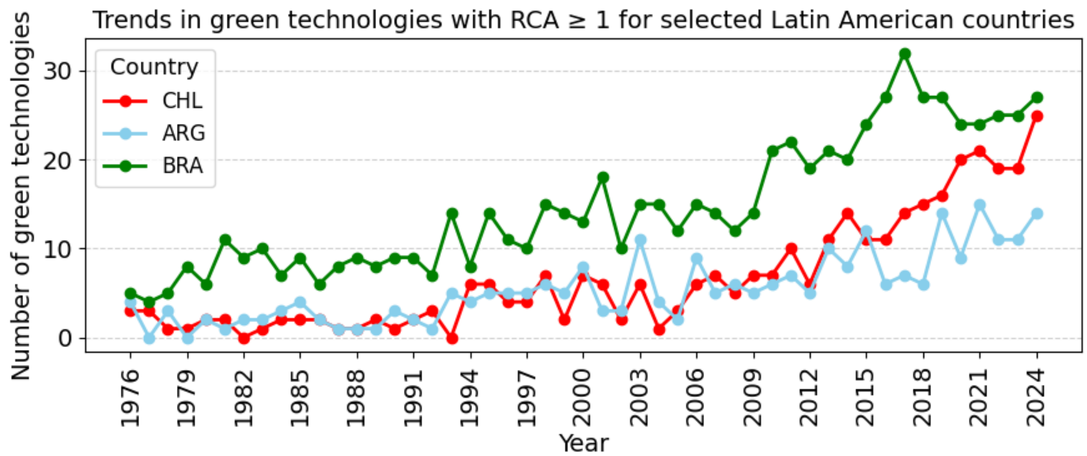
Complementing this relative picture, Figure 5.1.2 shows how from 2014 to 2024, Latin America in particular exhibits a clear acceleration of green specializations. Chile's own ratification of the Paris Agreement in 2017 likely contributed to this momentum, following Argentina's and Brazil's earlier ratifications in 2016 United Nations (2025) and, indeed, as Figure 5.1.3 shows, Chile, Brazil, and Argentina emerge as the regional leaders in green technological capabilities. We can see how Brazil established an early lead in the late 1970s with five to ten green technologies and then accelerated steadily, surpassing 20 competitive green technologies by 2010 and peaking above 30 around 2017. Conversely, Argentina and Chile began from near zero and remained relatively flat until the mid-1990s, after which they too climbed: Argentina reached double digits by 2015, while Chile's curve steepened most sharply post-2010, overtaking Argentina around 2014 and reaching 25 green technologies by 2024. This persistent upward trajectory, marked by Brazil long-term growth and the more recent surges in Chile and Argentina highlights how Latin America has progressively built and diversified its expertise in green technologies (Pérez-Hernández et al., 2025).

Figure 5.1.2: Global distribution of green technologies (RCA ≥ 1) by country (1985–2024)



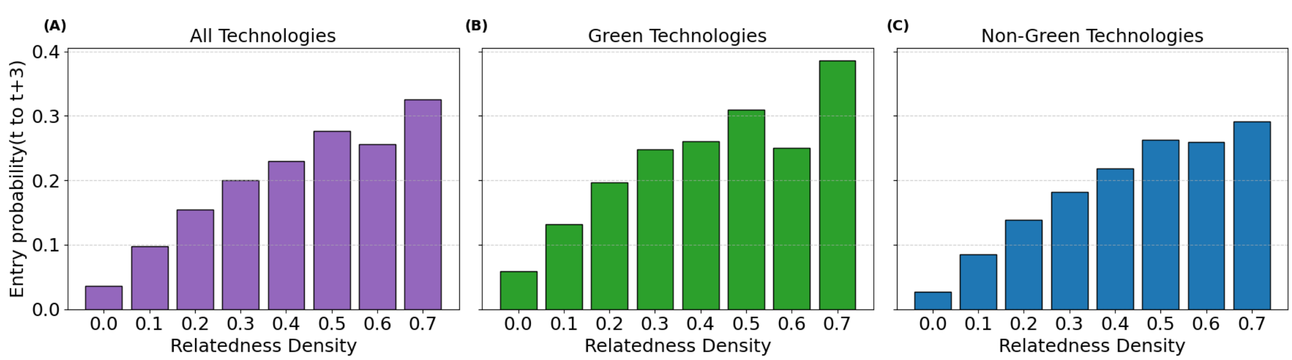
Note: Each panel shows the count of unique green CPC classes with revealed comparative advantage in: (A) 1985, (B) 2005, (C) 2014, (D) 2017, (E) 2022, and (F) 2024. Color intensity corresponds to the number of green technologies (darker = more), and light-grey hatched areas indicate countries with no recorded green technologies.

Figure 5.1.3: Trends in green technologies with RCA ≥ 1 for selected Latin American countries



To further illustrate the factors associated with green-technological entry, Figure 5.1.4 presents descriptive evidence on the relationship between relatedness density, KETs, and the likelihood of technological entry. In panel A (all technologies) the probability of entry increases monotonically with higher relatedness density. Panel B (green technologies) displays an even steeper slope, indicating that green innovation is particularly sensitive to structural relatedness. In contrast, panel C (non-green technologies) exhibit a more moderate increase, suggesting that entry into these domains may rely on broader or more generic capabilities. These results align with recent evidence showing that the development of green technologies strongly depends not only on related green capabilities but also on advancements in non-green technological domains (Barbieri et al., 2023).

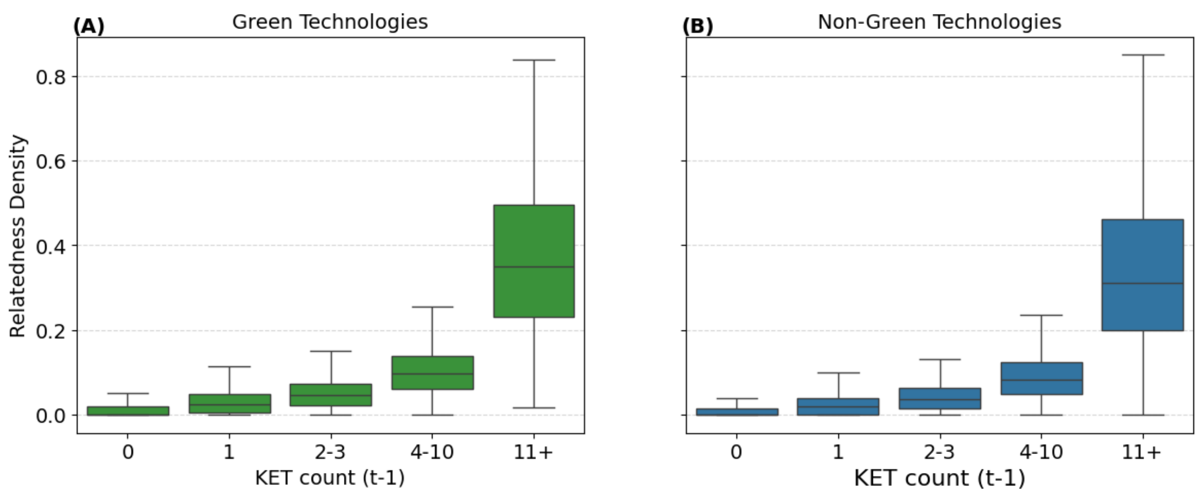
Figure 5.1.4: Probability of technological entry (*t* to *t+3*) as a function of relatedness density on cases where RCA = 0 at time *t*



Note: Each panel shows the average entry probability across relatedness density bins for: (A) all technologies, (B) green technologies, and (C) non-green technologies.

This asymmetric responsiveness is further supported by Figure 5.1.5, which examines the distribution of relatedness density across KET intensity bins. In both green and non-green technologies, higher KET counts at $t-1$ are associated with higher median relatedness density. However, the magnitude and variability are greater for green technologies. For example, in the highest KET intensity bin (11+), green technologies not only reach higher median values but also exhibit a wider interquartile range and more pronounced upper tails. This observation is consistent with Montresor and Quatraro (2020) who emphasize that regional KETs support transitions toward sustainable technologies and underline the critical role of pre-existing non-green knowledge in facilitating green diversification. Therefore, although KETs alone do not guarantee technological entry, their interaction with relatedness is especially influential in green contexts.

Figure 5.1.5: Distribution of relatedness density across KET intensity bins



Note: Each panel shows relatedness density distribution across KET count bins at t–1 for: (A) green technologies and (B) non-green technologies.

5.2 Econometric Analysis

As shown in descriptive analysis in Table 5.2.1, technological entry events are rare, among all cases with no activity in a given technology at time *t*, only 4% showed entry (i.e., presence) by *t+3*. Additionally, green technologies constitute less than a third (29%) of all countries, technology, year observations, indicating their relatively limited presence across the technological landscape. In Table 5.2.2 the correlation analysis reveals a strong positive association (r = 0.89) between relatedness density and KETs, this relationship is expected given the nature of both variables, as they reflect complementary dimensions of a country's technological capabilities and accumulated knowledge base.

Prior to estimating the regression models, multicollinearity was assessed using the Variance Inflation Factor (VIF). Most variables showed low VIF values, well below the conventional threshold of 5. However, relatedness density and KETs showed moderate multicollinearity (VIF ≈ 5.8). Despite this, both variables are retained in the model, as they capture theoretically distinct mechanisms.

Table 5.2.1: Descriptive statistics

Variable	N	Mean	SD	Min	Max
relatedness_density	385700	0,22	0,19	0,00	1,00
M_t	385700	0,04	0,19	0,00	1,00
gdp_per_capita	336623	23203,54	25380,87	93,75	196783,73
is_green	385700	0,29	0,46	0,00	1,00
ket_count_prev_year	385700	14,65	12,16	0,00	51,00
population_density	336357	268,99	818,91	1,83	7965,88
pm25_ug_m3	222642	20,82	12,22	4,90	79,04
fdi_net_inflows_usd	337687	16773917051,57	50766736365,57	-359330640340,00	733826501994,52

Source: Author's own elaboration.

Table 5.2.2: Pairwise correlation matrix

	Variable	1	2	3	4	5	6	7	8
1	relatedness_density	1,00							
2	M_t	0,09	1,00						
3	gdp_per_capita	0,34	0,02	1,00					
4	is_green	0,06	0,02	0,00	1,00				
5	ket_count_prev_year	0,89	0,05	0,37	0,00	1,00			
6	population_density	-0,08	-0,00	0,11	0,00	-0,07	1,00		
7	pm25_ug_m3	-0,34	-0,01	-0,50	0,00	-0,33	-0,03	1,00	
8	fdi_net_inflows_usd	0,26	0,01	0,16	0,00	0,27	0,06	-0,06	1,00

Source: Author's own elaboration.

The results from logistic regressions are shown in Table 5.2.3, which includes seven specifications (M1–M7). Model M1 includes all explanatory and control variables. All models include is_green to evaluate its effect, except for M7, which excludes it to assess whether green technologies behave differently across specifications. In addition, M7 isolates KETs to test its independent contribution, given the high correlation with relatedness density observed in the correlation matrix and VIF diagnostics. These models are further analyzed in the robustness check in Table 5.3.1 and Table 5.3.2. Together, they assess how relatedness and KETs activity shape the likelihood of technological entry, and whether green technologies may follow distinct diversification patterns.

Table 5.2.3: Logistic regression results for the whole dataset

	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**
relatedness_density	1,690***	1,717***	0,463***	0,387***	1,703***	0,423***	
	(0,030)	(0,025)	(0,010)	(0,011)	(0,023)	(0,008)	
is_green	0,011	0,045*	0,120***	0,138***	0,034+	0,137***	
	(0,024)	(0,020)	(0,020)	(0,024)	(0,019)	(0,019)	
gdp_per_capita	-0,107***		-0,172***				
	-0,018		(0,013)				
ket_count_prev_year	-1,447***	-1,489***			-1,464***		0,197***
	(0,033)	(0,027)			(0,025)		(0,009)
population_density	0,075***	0,046***					
	(0,010)	(0,009)					
pm25_ug_m3	0,062***			0,089***			
	(0,013)			(0,012)			
fdi_net_inflows_usd	-0,084***		-0,113***				
	(0,012)		(0,010)				
Year F. E	YES	YES	YES	YES	YES	YES	YES
Num | Obs	212800	316407	306033	222642	362558	362558	362558
Log-Likelihood	-33267	-48057	-48393	-35545	-55173	-57056	-58141
Pseudo-R^2	0,050	0,054	0,023	0,018	0,055	0,023	0,004

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Overall, the signs of the estimated coefficients are broadly consistent with theoretical expectations. Notably, the positive effect of relatedness density aligns with capability-based diversification theory (Balland et al., 2019; Foray et al., 2009). The negative signs for GDP per capita and FDI inflows are consistent with Boschma et al. (2025) and Dong et al. (2019), respectively, both potentially reflecting lock-in effects in mature economies (Boschma, 2021). The unexpected negative sign of KETs activity in several models contrasts with the findings of Montresor & Quatraro (2020), and may reflect overlapping variance with relatedness density or limited standalone explanatory power. However, the positive and significant effect of the is_green variable in the analysis aligns with their results, and the path dependency mechanism suggested by Mealy & Teytelboym (2022). Meanwhile, the positive and significant effect of $PM_{2.5}$ is consistent with Dong et al. (2022). Likewise, the positive and significant effect of population density aligns with Balland et al. (2018) and Balland et al. (2020).

Across all model specifications, relatedness density remains consistently positive and statistically significant, in line with prior evidence that relatedness fosters technological diversification within regions from Balland et al. (2019), confirming its central role in facilitating technological diversification. However, the magnitude of its effect varies notably across models, indicating some sensitivity to specification, likely due to its high correlation with KETs activity and moderate multicollinearity observed in the VIF analysis.

The role of green technologies, captured by the variable is_green, becomes more important in models that exclude KETs. For instance, in Model 3 and Model 4, where KET activity is not included, is_green is positive and highly significant, suggesting that the green character of a technology is associated with higher probabilities of entry. However, when KETs are introduced in Model 1, Model 2, and Model 5, the significance of is_green drops markedly. This pattern may reflect an underlying conceptual overlap: KETs are not necessarily green, but many green technologies rely on key enabling components (e.g., nanotech, advanced materials). Thus, the inclusion of KET activity may absorb part of the explanatory power initially captured by the is_green dummy, particularly in contexts where both indicators co-evolve.

Despite the strong correlation between both variables, the standalone explanatory power of KET activity is marginal, as evidenced in Model 7, where it yields a positive coefficient but the lowest pseudo-R^2 of all models. When introduced alongside relatedness density, KETs contribute little in terms of predictive accuracy, yet its presence shifts variance in a way that amplifies the magnitude of the relatedness effect. This suggests that the model reallocates explanatory weight toward relatedness density, which more robustly captures the embedded technological structure of regional innovation. Interestingly, Model 5 yields the highest pseudo-R^2 among all specifications, despite the negative and statistically significant coefficient of KETs. While accumulated KET capabilities may enhance technological advantages for green technologies (Montresor and Quatraro, 2020), they might also reinforce existing trajectories, limiting the exploration of more distant or emerging innovation domains (Hu et al., 2023).

Among the control variables, population density and $PM_{2.5}$ concentrations are positively and significantly associated with technological entry. This aligns with previous findings that pollution can stimulate people demand for green technologies, encouraging innovation in these areas (Dong et al., 2022). Furthermore, in line with Balland et al. (2018) who show that complex technologies concentrate in large cities due to knowledge-sharing dynamics, higher national population density may reflect similar agglomeration advantages at the country level. Conversely, GDP per capita and FDI inflows exhibit negative and statistically significant effects, which may reflect lock-in dynamics in economically advanced or already diversified regions, where entrenched development paths and specialization in mature sectors reduce the likelihood of engaging in novel technological trajectories. As Dong et al. (2022, p. 23) point out, "inventing new technologies requires external resources, i.e., capital and investment", and regions with stronger fiscal capacity or access to funding tend to concentrate innovation around existing capabilities. While these conditions favor innovation volume, they may constrain diversification into complex or green technologies when local systems are already oriented toward established sectors.

5.3 Robustness Analysis

To assess the robustness of the findings and explore heterogeneity between green and non-green technologies, as well as the behavior of relatedness density and KETs, seven logit specifications are estimated under three alternative fixed effects structures: year, CPC class, and combined year × CPC. Table 5.3.1 reports the results for green technologies, while Table 5.3.2 presents those for non-green technologies. In both cases, the seven most relevant models from the full set of estimations are detailed, distinguishing between those that include KET-related controls and those that do not, to enhance interpretability and allow for comparative insights.

Across both domains, as shown in Table 5.3.1 and Table 5.3.2, relatedness density consistently shows a positive and highly significant effect on the probability of technological entry, confirming its relevance as a robust predictor of diversification.

Importantly, it is observed that models excluding KETs (B1–B3 in Table 5.3.1 and D1–D3 in Table 5.3.2) result in lower pseudo-R^2 values across the board, reinforcing the argument that KET activity captures relevant aspects of the technological context. Nevertheless, KET itself does not provide predictive power. For instance, in green models, Model A4 includes only KET count and yields a pseudo-$R^2$of 0,000 compared to 0,030 in A3, where relatedness density is included.

Notably, the inclusion of KET-related variables amplifies the effect of relatedness density in both green and non-green contexts. In green technologies, the coefficient rises from 0.202 in B1 (without KET) to 1.436 in A3 (with KET); for non-green, from 0.507 in D1 to 1.897 in C3. A biserial correlation is used to test whether prior KET activity is associated with the level of relatedness in technological diversification. The negative result of –0.36 suggests that regions with KETs tend to enter less related technologies, indicating a more exploratory diversification pattern.

In terms of model performance, pseudo-R^2values are consistently higher in the non-green models (e.g., C1 = 0.063, C3 = 0.064) compared to green models (e.g., A1 = 0.029, A3 = 0.030). This may reflect the greater predictability of non-green technological entry, possibly due to more stable and entrenched innovation trajectories. In contrast, green diversification remains more heterogeneous and path breaking, potentially because entry into green technologies often requires overcoming higher technological complexity (Dong et al., 2022), as noted by Tinnefeld, Swart, and Fumagalli (2025), climate change mitigation technologies tend to be structurally related to high-engineering domains.

Table 5.3.1: Logistic regression results for green technologies: Models with and without KET controls

	With KET				**Without KET**		
	A1	**A2**	**A3**	**A4**	**B1**	**B2**	**B3**
relatedness_density	1,404***	1,431***	1,436***		0,202***	0,225***	0,153***
	(0,056)	(0,057)	(0,043)		(0,015)	(0,018)	(0,019)
gdp_per_capita	-0,121***	-0,079**				-0,147***	
	(0,031)	(0,029)				(0,023)	
ket_count_prev_year	-1,367***	-1.408***	-1,383***	0.046**			
	(0,061)	(0,061)	(0,047)	(0.016)			
population_density	0,078***	0,076***					
	(0,017)	(0,017)					
pm25_ug_m3	0,058**	0,065**					0,076***
	(0,022)	(0,022)					(0,020)
fdi_net_inflows_usd	-0,087***	-0,073***				-0,117***	
	(0,024)	(0,024)				(0,020)	
CPC class F. E	NO	YES	NO	YES	YES	YES	YES
Year F. E	YES	NO	YES	YES	YES	YES	NO
Num | Obs	62400	62400	106314	97614	97614	79919	65286
Log-Likelihood	-10921	-10897	-18265	-17794	-17707	-14823	-11610
Pseudo-R^2	0,029	0,029	0,030	0,000	0.005	0.006	0.003

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5.3.2: Logistic regression results for non-green technologies: Models with and without KET controls

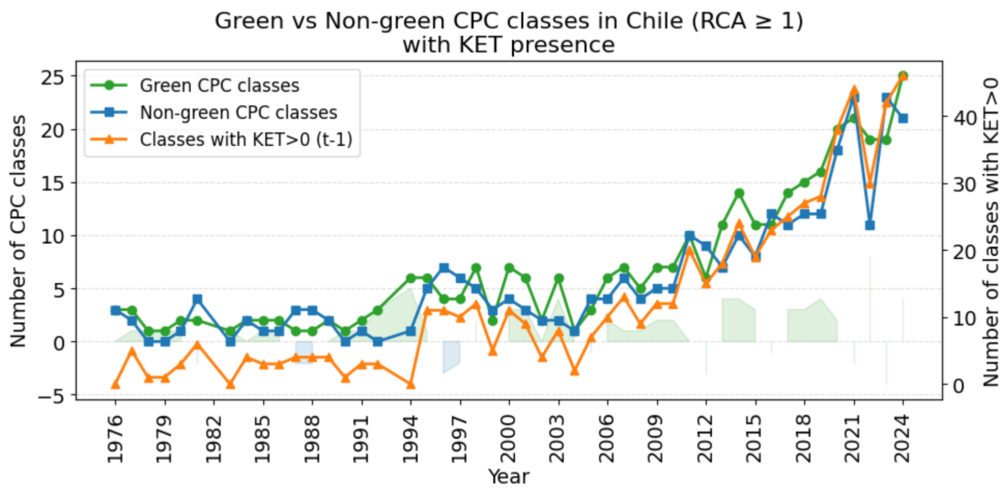
	With KET				Without KET		
	C1	**C2**	**C3**	**C4**	**D1**	**D2**	**D3**
relatedness_density	1,824***	1,231***	1,897***		0,507***	0.528***	0,484***
	(0,036)	(0,023)	(0,030)		(0,010)	(0,012)	(0,010)
gdp_per_capita	-0,102***					-0,159***	
	(0,022)					(0,016)	
ket_count_prev_year	-1,481***	-0,820***	-1,568***	0,275***			
	(0,039)	(0,024)	(0,032)	(0,011)			
population_density	0,073***	0,060***					
	(0,012)	(0,011)					
pm25_ug_m3	0,063**						
	(0,016)						
fdi_net_inflows_usd	-0,089***					-0,103***	
	(0,014)					(0,012)	
CPC class F. E	NO	YES	YES	YES	YES	YES	YES
Year F. E	YES	NO	YES	YES	NO	YES	YES
Num | Obs	150400	235197	214368	214368	272600	173905	214368
Log-Likelihood	-22212	-32569	-34195	-36197	-38236	-29842	-35457
Pseudo-R^2	0,063	0,049	0,064	0,009	0.032	0.030	0.029

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

5.4 Chile’s technological capabilities in green technologies

To assess Chile’s own green technologies strengths, Figure 5.4.1 shows that Chile’s capabilities in both green and non-green technologies has coincided with and been amplified by the steady expansion of key enabling technologies (Montresor & Quatraro, 2017). Since the early 2000s, green specializations have not only caught up but persistently outstripped non-green ones, signaling a structural shift in Chile’s innovation system toward environmental technologies. This evolution mirrors Montresor & Quatraro (2020) finding that “hybridization” with adjacent non-environmental knowledge lowers the barrier to green branching.

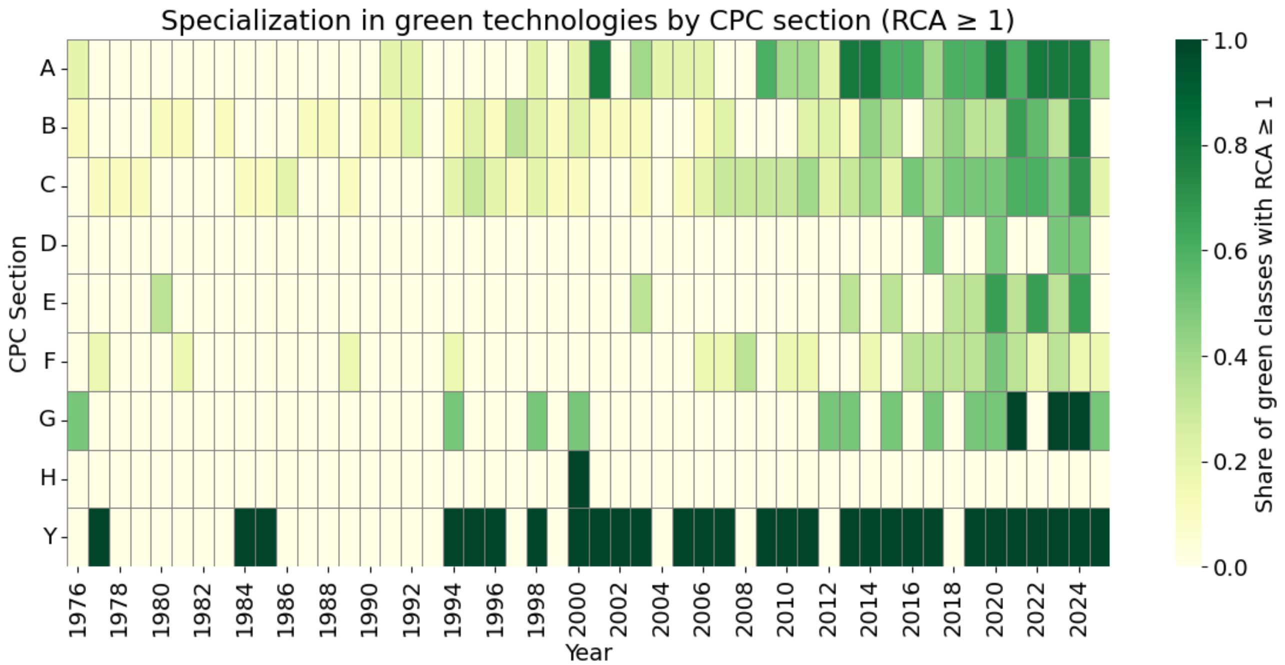
Figure 5.4.1: Green vs Non-green CPC classes in Chile (RCA ≥ 1) with KET presence



Note: Annual counts of green (●) vs. non-green (■) CPC classes with RCA ≥ 1 in Chile (left axis), shaded to show when green outpaces non-green and vice versa, alongside the number of classes with KET activity in t–1 (▲, right axis) from 1976 to 2024.

Chile’s green technological specialization, as shown in Figure 5.4.2, is notably concentrated in sections A, B, C, D, E and G reflecting a broadening yet focused alignment with sustainability-oriented domains. Section Y shows full specialization, driven by the consistent presence of class driven by the consistent presence of class Y02 (Technologies or applications for mitigation or adaptation against climate change) which is the only class from section Y present in the dataset for green technologies, highlighting a persistent trajectory toward green innovation. This pattern becomes more pronounced after 2017, the year Chile launched the PANCC, which positioned technological innovation and transfer as key drivers of its environmental agenda.

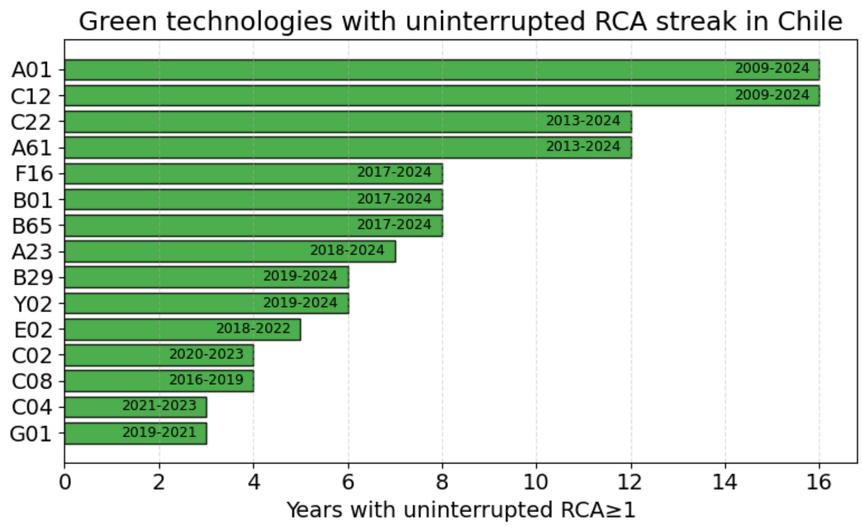
Figure 5.4.2: Specialization in green technologies by CPC section (RCA ≥ 1)



Note: Heatmap showing, for each CPC section and year in Chile, the share of green subsections in which Chile held RCA ≥ 1 (darker cells = higher share). CPC sections are: A Human necessities; B Performing operations; transporting; C Chemistry; metallurgy; D Textiles; paper; E Fixed constructions; F Mechanical engineering; lighting; heating; weapons; blasting; G Physics; H Electricity; Y General tagging of new technological developments; general tagging of cross-sectional technologies spanning over several sections of the IPC; technical subjects covered by former USPC cross-reference art collections (XRACs) and digests.

Figure 5.4.3 presents the Chile's green innovation landscape. It can be observed a path-dependent yet strategically adaptive structure, where natural resource-based strengths are transitioning toward sustainability. Agriculture and food technologies (A01, A23) remain strong, supported by plastics (C08) and sustainable packaging (B65, B29) likely used in fruit and vegetable exports. Biochemistry (C12) reflects biomass and wine-related processes, while A61 supports rural health, livestock and fishing. C22 and B01 highlight Chile's lead in low-emission mining. Water (C02, E02) and construction (C04) technologies address scarcity and infrastructure in mining regions. Mechanical systems (F16) and monitoring tools (G01) could enable decarbonization and circularity from renewables. The steady rise of climate tech (Y02) since 2019 signals Chile's growing ability to merge industrial legacy with green technologies, positioning it for low-carbon specialization.

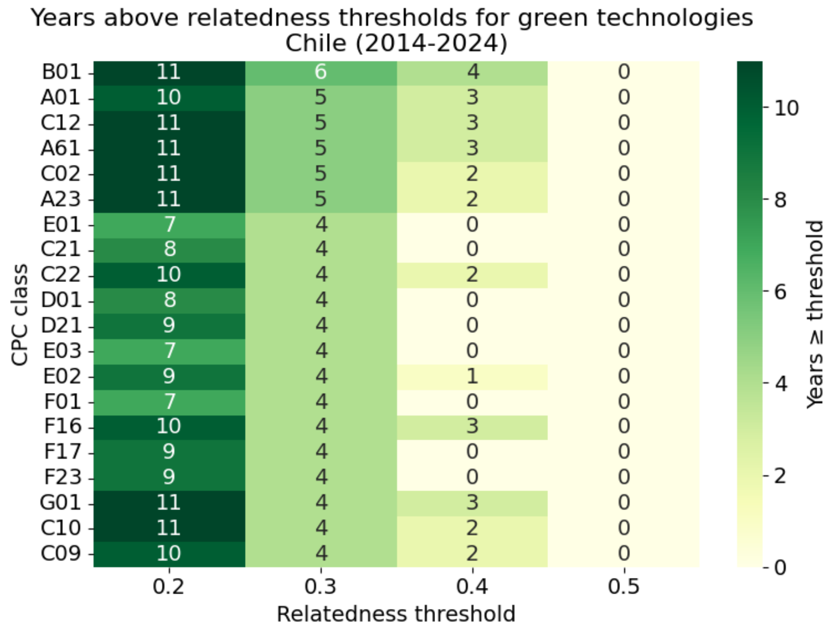
Figure 5.4.3: Green technologies with uninterrupted RCA streak in Chile



Note: Horizontal bar chart of the top 15 green CPC classes in Chile ranked by their longest uninterrupted streak of RCA ≥ 1 up to 2024. Each bar's length (x-axis) is the number of consecutive years the class maintained a revealed comparative advantage, with the start–end year labeled inside the bar.

Chile's most related green technological structure, shown in Figure 5.4.4, reflects a deeply rooted and strategically aligned system. B01 (chemical engineering) and C21/C22 (metallurgy) are relevant to mining decarbonization, enabling cleaner processing of copper, lithium, and iron through carbon capture, solvent extraction, and low-emission refining. C02 (water treatment) and E03 (water systems) further support sustainable extraction via desalination and tailings management. C09 (dyes, paints, polishes) and G01supports renewable systems through emissions monitoring and environmental data. E01 (roads, railways, bridges), E02 (hydraulic engineering), and C04 (construction) could enhance infrastructure resilience through low-carbon and climate-adaptive design. Land-based technologies A01, A23, and A61 reflect Chile's agroforestry strengths and innovation in plant science, aquaculture, and fire resilience. C12 (biochemistry) and D21 (pulp/paper) enable bio-based chemicals and materials, while D01 (fibers) supports sustainable textiles. Finally, mechanical classes F16, F01 (machines), F17 (gas/liquid storage), F23 (combustion), and C10 (fuels/pyrolysis) potentially enable hydrogen integration and retrofitting industrial systems.

Figure 5.4.4: Years above relatedness thresholds for green technologies in Chile (2014-2024)



Note: Heatmap of the top 20 green technologies in Chile, ranked by years with relatedness ≥ 0.3. Showing, for each class (rows) and each relatedness threshold (columns 0.2, 0.3, 0.4, 0.5), the number of years between 2014 and 2024 that its relatedness density exceeded that threshold (annotated values; darker = more years).

6 Discussion and public policy implications

The findings suggest that relatedness density is the primary driver for technological entry, consistent with Hidalgo et al. (2018). Green technologies, however, are less predictable and more dependent on the presence of both green and non-green existing capabilities. KETs, in turn, facilitate diversification, especially in green technologies and could help enable entry into less related technologies (Montresor & Quatraro, 2020).

These dynamics are also reflected in global patterns of specialization. While advanced economies have led green technology development, recent years reveal a growing diffusion of green capabilities toward Latin American countries. Although the region started from a low baseline, it has accelerated green diversification, particularly in Brazil, Argentina, and Chile.

Chile's own trajectory shows a shift toward sustainability not through entirely new technological paths, but by greening existing industrial capabilities. Since 2010, the country has rapidly expanded its green specialization, particularly in sectors tied to natural resources such as mining, agriculture, and water systems. The innovation structure remains path-dependent but strategically adaptive, enabling it to repurpose legacy strengths like metallurgy, chemical engineering, and biochemistry into low-carbon and circular solutions. This green trajectory has been accompanied by a steady rise in non-green and KET-related technologies, highlighting a broader technological deepening rather than a complete shift, with KETs playing a central role in enabling both paths.

These findings support that policy should focus on strengthening existing capabilities and their related domains to build competitive advantage in high value-added activities (Balland et al., 2019), while also promoting the development and strategic deployment of KETs as catalyst for both green and non-green diversification (Montresor & Quatraro, 2020). In emerging economies like Chile, where production often remains tied to low-complexity goods, basic skills and technological foundations can still enable movement toward more complex activities (Françoso et al., 2024). To foster this transition, it is essential to align sectoral incentives with regional policies, and to invest in skills development and absorptive capacity to understand, adapt, and generate new technologies particularly in structurally constrained and peripheral areas (Belmartino, 2022).

In this context, the findings of this work can directly inform CORFO's Programa Transforma Cambio Climático, part of the broader Transform Program for strategic sector development in Chile (Griffith-Jones et al., 2018), which aims to increase climate-related patenting 20% by 2033 (DEUMAN, 2023), while addressing key challenges such as limited evidence on technology feasibility, weak coordination among actors, and low levels of private-sector innovation. In this context, the analytical approach presented, based on patent data and technological relatedness, offers a useful lens for identifying areas where Chile may have greater potential to develop green technologies grounded in its existing technological capabilities. It also supports the program's emphasis on technology monitoring, providing a replicable framework to inform the identification and prioritization of high-potential domains.

Importantly, many of Chile's emerging green technologies are embedded in areas of high relatedness density, indicating a strong alignment with the country's existing technological capabilities and a robust foundation for future development. Building on these findings, it is recommended that the program integrate relatedness-based analysis as a strategic tool to more effectively leverage Chile's technological strengths, reduce uncertainty in identifying priority areas, and guide the allocation of resources toward domains with the highest potential, particularly those with high relatedness to existing resource-based strengths, such as green mining (e.g., low-emission metallurgy, water treatment), sustainable agriculture (e.g., biochemistry, bio-packaging), and resilient infrastructure (e.g., climate-adaptive construction, environmental monitoring). This methodology enables more precise targeting of technologies that fit within Chile's knowledge structure. By mapping technological proximity, the program can support a transition that builds on legacy capacities, accelerates low-emission and circular innovation, and promotes diversification through KETs. In turn, this approach facilitates convergence across technological domains, opening innovative pathways.

These insights should inform not only national innovation planning, but also the territorial implementation of strategies that reflect Chile's productive realities and regional strengths. In particular, the establishment of regional incubators, accelerators (European Union, 2025), and capacity-building initiatives in areas where green capabilities are already emerging can reinforce local innovation ecosystems and accelerate the transition toward a low-carbon economy.

As Chile advances its climate and industrial agendas, leveraging existing capabilities through data-driven and territorially sensitive innovation policies will be essential, not only to boost green competitiveness and patenting, but also to ensure a just, inclusive, and sustainable transformation aligned with the country's long-term development priorities.

7 Conclusion

Climate change is one of the greatest ecological and social challenges of the twenty-first century. The Earth's climate is now changing faster than at any point in the history of modern civilization, due to human activities (Dietz et al., 2020), causing widespread and accelerating impacts on nature and people (Calvin et al., 2023). Societies face two key responses: adaptation, which reduces vulnerability to impacts, and mitigation, which seeks to limit future warming by cutting GHG emissions. In this context, green technologies are central to achieving a low-carbon future.

This thesis offers new evidence on the drivers of green technological development using patent data spanning from 1976 to 2025. Using a logistic regression model, it is evaluated the influence of relatedness density and KETs in shaping technological entry. The findings aligns with the literature by showing that relatedness density is a driver of new technological specialization (Balland et al., 2019; Hidalgo et al., 2007, 2018). Green technologies, however, exhibit lower predictability in entry patterns and appear more sensitive to the presence of both green and non-green capabilities, underscoring their greater complexity and path dependency (Mealy & Teytelboym, 2022). In this context, KETs may play an enabling role by facilitating related and unrelated diversification, especially green technologies that are more distant or complex (Dong et al., 2022; Montresor & Quatraro, 2020). These results remain robust after controlling environmental and economic variables, including population density, pollution levels, GDP per capita, and foreign direct investment.

It is also observed a growing green innovation capacity in Latin America, where inventive capacity in green technologies has steadily increased, positioning the region as a potential innovation leader due to its strong resource base (Pérez-Hernández et al., 2025). In Chile, instead of a full transformation of its productive matrix, there has been a sustained greening of existing industrial strengths, supported by progress in both green and non-green technologies and KETs.

These insights reinforce the importance of place-based innovation strategies that build existing capabilities. Rather than attempting to start from scratch, policymakers should support technological upgrading within existing structures, while avoiding over-specialization that could trap economies in low-complexity activities (Boschma, 2021).

In Chile, this implies not only continuing to modernize but also leveraging resource-based sectors as platforms for innovation (Li et al., 2024; Li & Iammarino, 2024). At the same time, it is crucial to explore adjacent and more complex technologies to enhance diversification potential and generate higher value-added output (Balland et al., 2019). Given the country's regional disparities, decentralized innovation strategies are essential. Local governments should have the capacity and autonomy to design policies tailored to their industrial profiles (Ascani et al., 2020), supported by targeted investments in human capital to translate raw knowledge into applied innovation and long-term technological upgrading (Bergamini & Zachmann, 2021; Colombelli & Quatraro, 2019).

While this study provides valuable insights, it has several limitations that should be addressed in future research. First, it relies exclusively on patent data, which captures only formal innovation and may overlook other relevant aspects of technology and innovation activities. Second, the use of 2-digit CPC codes, which are relatively broad and may obscure important intra-sectoral dynamics and finer technological nuances. Third, the national-level focus may mask significant subnational heterogeneity, particularly in countries with diverse regional industrial profiles such as Chile. Finally, the study does not incorporate measures of technological complexity, which are essential for assessing the strategic value of diversification.

Future research should address these limitations by incorporating complementary data sources such as industry, occupation or scientific field datasets (Balland et al., 2020), and adopting more detailed patent classifications at both the Latin American and national levels. Subnational analyses are also essential to reveal regional specialization patterns and cooperation opportunities. Importantly, adapting the smart specialization framework to the Latin American context, through the development of a regionally disaggregated dataset (e.g., by regions in Chile or provinces in Argentina), would enable more accurate assessments of relatedness and complexity. This would support the identification of strategic complementarities and inform policies aimed at fostering both green and non-green innovation across the region. As part of this effort, and as Belmartino (2022) highlights, it is important to advance the construction of a specific nomenclature for green products, technologies, and occupations within such datasets, enabling more precise identification and policy targeting.

8 References

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9 Appendix 1 Green technologies

Class	Title
A01	AGRICULTURE; FORESTRY; ANIMAL HUSBANDRY; HUNTING; TRAPPING; FISHING
A23	FOODS OR FOODSTUFFS; TREATMENT THEREOF, NOT COVERED BY OTHER CLASSES
A43	FOOTWEAR
A47	FURNITURE; DOMESTIC ARTICLES OR APPLIANCES; COFFEE MILLS; SPICE MILLS; SUCTION CLEANERS IN GENERAL
A61	MEDICAL OR VETERINARY SCIENCE; HYGIENE
B01	PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL
B03	SEPARATION OF SOLID MATERIALS USING LIQUIDS OR USING PNEUMATIC TABLES OR JIGS; MAGNETIC OR ELECTROSTATIC SEPARATION OF SOLID MATERIALS FROM SOLID MATERIALS OR FLUIDS; SEPARATION BY HIGH-VOLTAGE ELECTRIC FIELDS
B09	DISPOSAL OF SOLID WASTE; RECLAMATION OF CONTAMINATED SOIL
B22	CASTING; POWDER METALLURGY
B29	WORKING OF PLASTICS; WORKING OF SUBSTANCES IN A PLASTIC STATE IN GENERAL
B30	PRESSES
B62	LAND VEHICLES FOR TRAVELLING OTHERWISE THAN ON RAILS
B63	SHIPS OR OTHER WATERBORNE VESSELS; RELATED EQUIPMENT
B65	CONVEYING; PACKING; STORING; HANDLING THIN OR FILAMENTARY MATERIAL
C02	TREATMENT OF WATER, WASTEWATER, SEWAGE, OR SLUDGE
C03	GLASS; MINERAL OR SLAG WOOL
C04	CEMENTS; CONCRETE; ARTIFICIAL STONE; CERAMICS; REFRACTORIES
C05	FERTILISERS; MANUFACTURE THEREOF
C08	ORGANIC MACROMOLECULAR COMPOUNDS; THEIR PREPARATION OR CHEMICAL WORKING-UP; COMPOSITIONS BASED THEREON
C09	DYES; PAINTS; POLISHES; NATURAL RESINS; ADHESIVES; COMPOSITIONS NOT OTHERWISE PROVIDED FOR; APPLICATIONS OF MATERIALS NOT OTHERWISE PROVIDED FOR
C10	PETROLEUM, GAS OR COKE INDUSTRIES; TECHNICAL GASES CONTAINING CARBON MONOXIDE; FUELS; LUBRICANTS; PEAT

C12	BIOCHEMISTRY; BEER; SPIRITS; WINE; VINEGAR; MICROBIOLOGY; ENZYMOLOGY; MUTATION OR GENETIC ENGINEERING
C21	METALLURGY OF IRON
C22	METALLURGY; FERROUS OR NON-FERROUS ALLOYS; TREATMENT OF ALLOYS OR NON-FERROUS METALS
D01	NATURAL OR MAN-MADE THREADS OR FIBRES; SPINNING
D21	PAPER-MAKING; PRODUCTION OF CELLULOSE
E01	CONSTRUCTION OF ROADS, RAILWAYS, OR BRIDGES
E02	HYDRAULIC ENGINEERING; FOUNDATIONS; SOIL SHIFTING
E03	WATER SUPPLY; SEWERAGE
F01	MACHINES OR ENGINES IN GENERAL; ENGINE PLANTS IN GENERAL; STEAM ENGINES
F02	COMBUSTION ENGINES; HOT-GAS OR COMBUSTION-PRODUCT ENGINE PLANTS
F16	ENGINEERING ELEMENTS AND UNITS; GENERAL MEASURES FOR PRODUCING AND MAINTAINING EFFECTIVE FUNCTIONING OF MACHINES OR INSTALLATIONS; THERMAL INSULATION IN GENERAL
F17	STORING OR DISTRIBUTING GASES OR LIQUIDS
F23	COMBUSTION APPARATUS; COMBUSTION PROCESSES
F27	FURNACES; KILNS; OVENS; RETORTS
G01	MEASURING; TESTING
G08	SIGNALLING
H01	ELECTRIC ELEMENTS
Y02	TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE

10 Appendix 2 Key Enable Technologies

Class	Title
A21	BAKING; EDIBLE DOUGHS
A22	BUTCHERING; MEAT TREATMENT; PROCESSING POULTRY OR FISH
A23	FOODS OR FOODSTUFFS; TREATMENT THEREOF, NOT COVERED BY OTHER CLASSES
A24	TOBACCO; CIGARS; CIGARETTES; SIMULATED SMOKING DEVICES; SMOKERS' REQUISITES
A41	WEARING APPAREL
A42	HEADWEAR
A43	FOOTWEAR

B01	PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL
B02	CRUSHING, PULVERISING, OR DISINTEGRATING; PREPARATORY TREATMENT OF GRAIN FOR MILLING
B03	SEPARATION OF SOLID MATERIALS USING LIQUIDS OR USING PNEUMATIC TABLES OR JIGS; MAGNETIC OR ELECTROSTATIC SEPARATION OF SOLID MATERIALS FROM SOLID MATERIALS OR FLUIDS; SEPARATION BY HIGH-VOLTAGE ELECTRIC FIELDS
B05	SPRAYING OR ATOMISING IN GENERAL; APPLYING FLUENT MATERIALS TO SURFACES, IN GENERAL
B06	GENERATING OR TRANSMITTING MECHANICAL VIBRATIONS IN GENERAL
B07	SEPARATING SOLIDS FROM SOLIDS; SORTING
B08	CLEANING
B21	MECHANICAL METAL-WORKING WITHOUT ESSENTIALLY REMOVING MATERIAL; PUNCHING METAL
B22	CASTING; POWDER METALLURGY
B23	MACHINE TOOLS; METAL-WORKING NOT OTHERWISE PROVIDED FOR
B24	GRINDING; POLISHING
B25	HAND TOOLS; PORTABLE POWER-DRIVEN TOOLS; MANIPULATORS
B26	HAND CUTTING TOOLS; CUTTING; SEVERING
B27	WORKING OR PRESERVING WOOD OR SIMILAR MATERIAL; NAILING OR STAPLING MACHINES IN GENERAL
B28	WORKING CEMENT, CLAY, OR STONE
B30	PRESSES
B31	MAKING ARTICLES OF PAPER, CARDBOARD OR MATERIAL WORKED IN A MANNER ANALOGOUS TO PAPER; WORKING PAPER, CARDBOARD OR MATERIAL WORKED IN A MANNER ANALOGOUS TO PAPER
B32	LAYERED PRODUCTS
B41	PRINTING; LINING MACHINES; TYPEWRITERS; STAMPS
B42	BOOKBINDING; ALBUMS; FILES; SPECIAL PRINTED MATTER
B44	DECORATIVE ARTS
B65	CONVEYING; PACKING; STORING; HANDLING THIN OR FILAMENTARY MATERIAL

B67	OPENING, CLOSING; OR CLEANING; BOTTLES, JARS OR SIMILAR CONTAINERS; LIQUID HANDLING
B68	SADDLERY; UPHOLSTERY
B82	NANOTECHNOLOGY
C01	INORGANIC CHEMISTRY
C02	TREATMENT OF WATER, WASTEWATER, SEWAGE, OR SLUDGE
C04	CEMENTS; CONCRETE; ARTIFICIAL STONE; CERAMICS; REFRACTORIES
C07	ORGANIC CHEMISTRY
C08	ORGANIC MACROMOLECULAR COMPOUNDS; THEIR PREPARATION OR CHEMICAL WORKING-UP; COMPOSITIONS BASED THEREON
C09	DYES; PAINTS; POLISHES; NATURAL RESINS; ADHESIVES; COMPOSITIONS NOT OTHERWISE PROVIDED FOR; APPLICATIONS OF MATERIALS NOT OTHERWISE PROVIDED FOR
C12	BIOCHEMISTRY; BEER; SPIRITS; WINE; VINEGAR; MICROBIOLOGY; ENZYMOLOGY; MUTATION OR GENETIC ENGINEERING
C13	SUGAR INDUSTRY
C14	SKINS; HIDES; PELTS; LEATHER
C22	METALLURGY; FERROUS OR NON-FERROUS ALLOYS; TREATMENT OF ALLOYS OR NON-FERROUS METALS
C23	COATING METALLIC MATERIAL; COATING MATERIAL WITH METALLIC MATERIAL; CHEMICAL SURFACE TREATMENT; DIFFUSION TREATMENT OF METALLIC MATERIAL; COATING BY VACUUM EVAPORATION, BY SPUTTERING, BY ION IMPLANTATION OR BY CHEMICAL VAPOUR DEPOSITION, IN GENERAL; INHIBITING CORROSION OF METALLIC MATERIAL OR INCRUSTATION IN GENERAL
D01	NATURAL OR MAN-MADE THREADS OR FIBRES; SPINNING
D02	YARNS; MECHANICAL FINISHING OF YARNS OR ROPES; WARPING OR BEAMING
D03	WEAVING
D04	BRAIDING; LACE-MAKING; KNITTING; TRIMMINGS; NON-WOVEN FABRICS
D05	SEWING; EMBROIDERING; TUFTING
D06	TREATMENT OF TEXTILES OR THE LIKE; LAUNDERING; FLEXIBLE MATERIALS NOT OTHERWISE PROVIDED FOR
D21	PAPER-MAKING; PRODUCTION OF CELLULOSE

E01	CONSTRUCTION OF ROADS, RAILWAYS, OR BRIDGES
E02	HYDRAULIC ENGINEERING; FOUNDATIONS; SOIL SHIFTING
E21	EARTH OR ROCK DRILLING; MINING
F04	POSITIVE - DISPLACEMENT MACHINES FOR LIQUIDS; PUMPS FOR LIQUIDS OR ELASTIC FLUIDS
F16	ENGINEERING ELEMENTS AND UNITS; GENERAL MEASURES FOR PRODUCING AND MAINTAINING EFFECTIVE FUNCTIONING OF MACHINES OR INSTALLATIONS; THERMAL INSULATION IN GENERAL
F21	LIGHTING
F26	DRYING
G01	MEASURING; TESTING
G02	OPTICS
G05	CONTROLLING; REGULATING
G06	COMPUTING; CALCULATING OR COUNTING
G07	CHECKING-DEVICES
G08	SIGNALLING
H01	ELECTRIC ELEMENTS
H02	GENERATION; CONVERSION OR DISTRIBUTION OF ELECTRIC POWER
H03	ELECTRONIC CIRCUITRY
H05	ELECTRIC TECHNIQUES NOT OTHERWISE PROVIDED FOR

UNIVERSIDAD DE CONCEPCIÓN – FACULTAD DE INGENIERÍA

RESUMEN DE MEMORIA DE TITULO

Departamento	: Departamento de Ingeniería Industrial
Carrera	: Ingeniería Civil Industrial
Nombre del memorista	: Leonardo Antonio Cruces González
Título de la memoria	: Evaluation of technological capabilities related to green technologies in Chile
Fecha de la presentación oral	: 22 de Julio, 2025
Profesor(es) Guía	: Carlos Camilo Navarrete Lizama
Profesor(es) Revisor(es)	: Cristian Alejandro Mardones Poblete
Concepto	:
Calificación	:

Resumen

El cambio climático es un desafío mundial urgente que requiere esfuerzos coordinados de los gobiernos para impulsar el desarrollo sostenible. Entre las políticas disponibles, la especialización inteligente ha ganado relevancia para fomentar la innovación verde mediante el aprovechamiento de capacidades nacionales, especialmente en la Unión Europea. Sin embargo, su efectividad en economías emergentes ha sido poco estudiada. Esta tesis analiza los factores que impulsan el desarrollo tecnológico verde a nivel global entre 1976 y 2025. A partir de datos de patentes, se mapean las capacidades tecnológicas de los países, identificando elementos que influyen en la aparición de nuevas tecnologías verdes. Los resultados indican que una mayor relatedness density, que muestra la proximidad entre capacidades existentes, se asocia positivamente al surgimiento de tecnologías verdes. Estas tecnologías, sin embargo, presentan dinámicas más complejas y menos predecibles, al depender de capacidades previas verdes y no verdes, lo que evidencia dependencia del camino. Aunque las economías avanzadas lideran la innovación verde, regiones emergentes como América Latina fortalecen sus capacidades tecnológicas. El caso de Chile refleja una transición progresiva hacia tecnologías verdes, basada en fortalezas existentes. Los hallazgos resaltan la necesidad de estrategias territoriales que impulsen capacidades existentes para una transición verde inclusiva y sostenible.