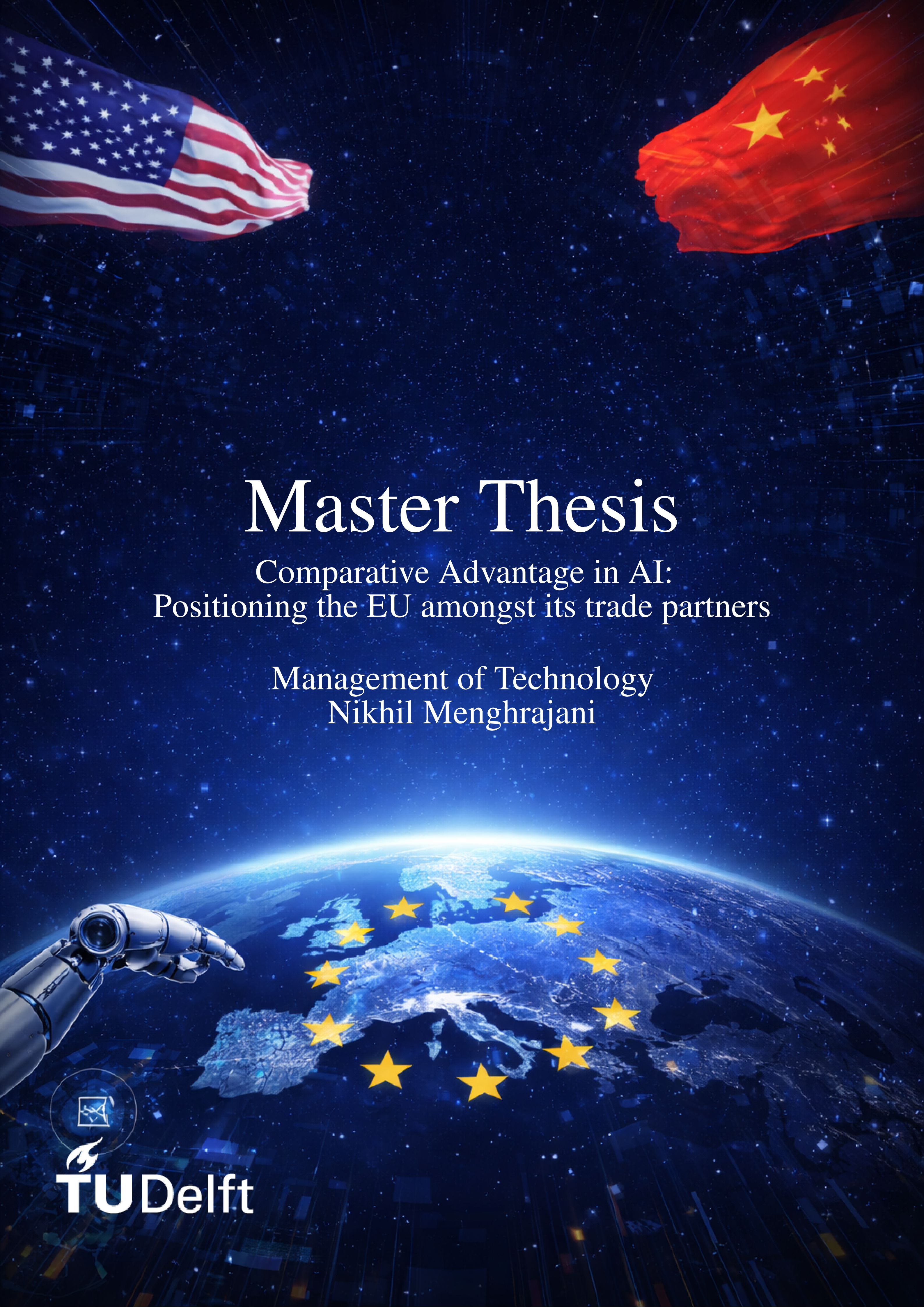

Master Thesis

Comparative Advantage in AI: Positioning the EU amongst its trade partners

Management of Technology

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TU Delft

Comparative Advantage in AI: Positioning the EU amongst its trade partners

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Abstract

This thesis examines how the accumulation of AI-related knowledge has shaped the comparative advantage of countries in global trade since 2010 and assesses the implications for the technological sovereignty goals of the EU. Using an extended Heckscher Ohlin Vanek (HOV) framework with factor-content corrections proposed by Trefler and Zhu (2010), AI and non-AI patent stocks are integrated alongside traditional labour and capital stock endowments to analyse trade patterns across 45 countries from 2010 to 2021. The empirical analysis reveals strong support for the HOV framework, with sign test achieving 90% success rate and patents performing better than traditional factors of labour and capital in predicting trade patterns. The results demonstrate that as of 2021, the US, China, and Korea hold a comparative advantage in AI patents, while the EU does not. Within the EU, only the Netherlands, Sweden, and Finland attempt to maintain a comparative advantage, whereas major economies, including Germany, France, and Italy, lag. The relative factor abundance in AI patents for the EU deteriorated between 2012 and 2019, coinciding with the rise of China and reflecting internal fragmentation among member states. These findings indicate that the lack of comparative advantage in AI for the EU creates strategic vulnerabilities that undermine its technological sovereignty goals, particularly as AI becomes embedded in critical infrastructures. For the EU to achieve genuine strategic autonomy, regulatory leadership must be complemented by strengthened capabilities in AI-enabling hardware, reduced dependence on foreign AI intellectual property, improved translation of research into commercial innovation, and cohesion-oriented policies addressing internal capability divergence. The research contributes methodologically by demonstrating that accumulated knowledge stocks measured through patents constitute formable factors that shape comparative advantage, and empirically by providing the first comprehensive HOV analysis of AI-related patent endowments across major trading economies.

Executive Summary

Artificial Intelligence (AI) has rapidly emerged as a transformative General Purpose Technology (GPT) with increasing applications across multiple industries. As AI continues to diffuse through the global economy, fundamental questions arise about which countries possess the knowledge stocks underpinning this technological paradigm and what this means for international competitiveness. For the European Union (EU), these questions carry urgency given its recent ambitions for technological sovereignty and concerns about excessive dependence on foreign technological capabilities, especially from the United States (US) and China. This thesis addresses this gap by asking: How has the evolution of comparative advantage in AI since 2010 reshaped the global trade landscape, and what does the relative position of the EU imply for its ability to achieve technological sovereignty?

The research employs the HOV framework, which predicts that countries export goods embodying the factors of production in which they are relatively abundant. Building on methodological advances by Trefler and Zhu (2010) that incorporate technology differences and trade in intermediate inputs, the analysis examines four factor endowments: AI-related patent stock, non-AI-related patent stock, labour, and capital stock. Patent data cover 45 countries from 2010 to 2021, with AI-related patents identified using the World Intellectual Property Organization (WIPO) AI Index queries.

The descriptive analysis reveals concerning trends for the EU. While AI intensity has risen globally since 2014, the share of the EU in global AI patents fell by approximately 9 percentage points between 2010 and 2021. This decline exceeds the loss in non-AI patents, indicating that Europe is falling behind faster in AI than in innovation overall. China moved in the opposite direction, with its global share of AI patents rising dramatically to overtake the EU by 2021. Industry-level analysis shows that nearly 50% of global AI patents originate in the computer, electronics, and optics sector, which serves as the primary channel for AI diffusion throughout the economy, and the decline in the share of global AI patents is steepest for the EU here.

The empirical tests demonstrate that the HOV framework performs well for AI-related patent endowments. Sign tests achieve 90% success rates, meaning that in 90% of cases, countries are net exporters of factors in which they are relatively abundant. Notably, AI-related and non-AI-related patents perform better than traditional factors like labour and capital stock in predicting trade patterns. This finding validates the use of accumulated knowledge stocks measured through patents as meaningful drivers of comparative advantage in trade.

Building on these empirical validations, the comparative advantage analysis reveals that as of 2021, the US, China, and Korea hold a clear comparative advantage in AI-related patents relative to non-AI-related patents, while the EU does not. The finding shows that the EU consumes more goods and services embodying AI-patents than it produces. The period of sharpest deterioration, from 2012 to 2019, coincides precisely with the rapid accumulation of AI capabilities of China and reveals growing internal fragmentation within the EU, with the Netherlands, Sweden, and Finland still attempting to maintain some comparative advantage while larger economies like Germany, France, and Italy lag.

These findings carry four key implications for the technological sovereignty strategies of the EU. First, the EU must prioritise developing its computer, electronics, and optics sector as essential infrastructure for economy-wide AI diffusion. Second, reducing technological dependence in AI-related models, algorithms, and intellectual property has become imperative given the pervasive nature of AI and the changing geopolitical environment. Third, addressing the bottleneck in translating research excellence into commercial innovation represents the most immediate opportunity, as the EU maintains strength in AI publications but lags in patents and commercialisation. Fourth, internal divergence in AI capabilities threatens collective strategic autonomy and requires cohesion-oriented policies to prevent further division in Europe in AI development.

While the EU has launched numerous initiatives, including the European Chips Act, AI Factories, data space strategies, and innovation support programs, these measures remain modest in scale compared to investments by the US and China and often operate as fragmented interventions rather than coherent pipeline strategies. The research recommends expanding hardware policies beyond semiconductors to encompass AI chip design and accelerators, mandating data contribution requirements from large platforms to build European data commons, consolidating innovation support around clear objectives for converting research into patents and globally competitive firms, and strategically distributing AI infrastructure investments to promote convergence among member states.

This thesis contributes to international trade theory by demonstrating that formable knowledge factors measured through patents shape comparative advantage through the same mechanisms operating for traditional production factors. It extends the HOV literature by incorporating AI-specific knowledge stocks and broadening geographic coverage to include China alongside EU and US comparisons. For policy, it provides the first empirical assessment linking AI patent endowments to comparative advantage and technological sovereignty, offering data-grounded evidence that regulatory leadership of the EU must be complemented by strengthened technological capabilities to achieve genuine strategic autonomy in the AI era.

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Acronyms

AI Artificial Intelligence

ALP Algorithmic Links with Probabilities

ECB European Central Bank

EIC European Innovation Council

EPO European Patent Office

ERC European Research Council

EU European Union

FDA U.S. Food and Drug Administration

GPT General Purpose Technology

GPUs Graphics Processing Units

HO Heckscher and Ohlin

HOV Heckscher Ohlin Vanek

ICIO Inter-Country Input-Output

ICT Information and Communication Technologies

IIO International Input Output

IMEC Interuniversity Microelectronics Centre

IOM Industry of Manufacture

IPC International Patent Classification

IPCEI Important Projects of Common European Interest

ISIC International Standard Industrial Classification

JPO Japan Patent Office

LLMs Large Language Models

MOT Management of Technology

MSCA Marie Skłodowska-Curie Action

OECD Organisation for Economic Co-operation and Development

OLS Ordinary Least Squares

OTC OECD Technology Concordance

PCT Patent Cooperation Treaty

PIM Perpetual Inventory Method

SMEs Small and Medium Enterprises

SOU Sector of Use

US United States

USPTO United States Patent and Trademark Office

WIOD World Input Output Data

WIPO World Intellectual Property Organization

YTC Yale Technology Concordance

1 Introduction

This chapter establishes the research context, gaps, research questions, and structure of the thesis. Section 1.1 is the main introduction, which situates the research within the broader context of Artificial Intelligence as an emerging General Purpose Technology and examines how international trade theory, particularly the Heckscher-Ohlin-Vanek framework, provides a lens through which to analyse the distribution of AI-related knowledge stocks across countries. It discusses how accumulated knowledge can be treated as a formable factor endowment and why this perspective is particularly relevant for understanding the competitive position of the EU and its technological sovereignty ambitions. Section 1.2 articulates the main research question and the five research sub-questions that structure the empirical analysis. Section 1.3 demonstrates the connection between this research and the Management of Technology program. Lastly, Section 1.4 provides an overview of the remaining chapters and presents a structured roadmap for the thesis.

1.1. Research Context

Regular interaction with AI has become increasingly common as it continues to be embedded in everyday life. It could be through personalised advertisements, virtual personal assistants, or Large Language Models (LLMs). AI has increasing applications across multiple industries, including banking, healthcare, and transportation. In 2023, the U.S. Food and Drug Administration (FDA) approved 223 AI-enabled medical devices, up from just 6 in 2015, while Waymo and Baidu started operating autonomous rides (Maslej et al., 2025). AI is also rapidly evolving, with performance on demanding benchmarks continuing to rise, and recent models even outperforming humans in programming tasks with limited time budgets (Maslej et al., 2025). It is further fostering complementarities by enabling new forms of automation and problem-solving across sectors.

Various economists have debated the role of technological change in driving long-term economic growth. Despite their different theories, they all agree that it is essential. Old neoclassical growth theory treats technological change as an exogenous factor to the production function (Abramovitz, 1956; Hahn & Matthews, 1964; Solow, 1957). New growth theory, on the other hand, attempts to endogenise technical change (Romer, 1996), while others examine the sources and procedures of this innovation (Rosenberg, 1983). North and Thomas (1973) even argue that technological progress and factor accumulation are “not causes of growth; they are growth”.

Over time, a post-Schumpeterian perspective has emerged, which posits that growth is driven by “technological systems” in long waves, followed by periods of stagnation, a concept coined by Schumpeter as “creative destruction” (Freeman, 1986; Schumpeter, 1950). These systems are not single inventions but interlinked technologies that can be widely adopted across industries that came to be termed as GPT. Bresnahan and Trajtenberg (1995) proposed the following salient features of GPTs: (a) they perform a general function across sectors, (b) they display continuous dynamism and improvement, and (c) they generate innovation complementarities. Classic examples include steam power, electricity, and Information and Communication Technologies (ICT). Within this framework, given its widespread diffusion into daily economic activity, AI can be interpreted as a new GPT driving a new Schumpeterian wave.

The post-Schumpeterian perspective can also be linked to the three-part Pavitt taxonomy of innovation patterns, i.e., supplier-dominated, production-intensive, and science-based (Pavitt, 1984). According to Archibugi (2001), each Schumpeterian wave can be linked to the emergence of new types of firms whose pattern of innovative activities can be described by the Pavitt taxonomy. The emergence of science-based firms such as OpenAI and Anthropic, alongside the rapid reorientation of incumbent firms across industries toward AI, is consistent with the patterns described here and also supports treating AI as distinct from broader ICT.

If AI is a new GPT, an immediate question from an international economics perspective is which countries dispose of the knowledge stocks that underpin this technological paradigm. This question is central because GPTs shape not only productivity growth but also the international distribution of economic activity. As a GPT, AI is expected to influence not only the diffusion of technology across sectors through the production and trade of AI-enabled goods and services, but also to alter productivity levels within sectors as firms integrate AI into their production processes. This dual impact on both trade patterns and within-sector productivity makes understanding the distribution of AI knowledge stocks particularly relevant for assessing future patterns of economic growth.

International trade theory provides a natural framework for analysing this question. The Heckscher and Ohlin (HO) model, developed by (Heckscher, 1919) and (Ohlin, 1924), has been the predominant framework in trade theory for much of the twentieth century. This model explains trade patterns based on differences in factor endowments across countries, understood as differences in the availability of resources and other inputs to production, such as labour, land, and capital. The standard HO model assumes identical production technologies but different factor endowments. Its main prediction is that each country specialises in and exports the good that intensively uses its relatively abundant factor. This result hinges on the concept of comparative advantage: international trade is driven not by overall productivity differences, but by relative factor abundance and the suitability of those factors for particular forms of production.

The HO model can be contrasted with the earlier Ricardian framework. Ricardo

(1817) attributed comparative advantage to technological differences across countries, treating technology as an exogenous determinant of productivity. However, it relied on a single factor of production and did not analyse how multiple factor endowments interact to shape trade patterns. The HO model addressed this limitation by permitting cross-country variation in factor endowments but went back to assuming uniform production technologies across countries.

Vanek (1968) further extended the HO framework by incorporating multiple goods and multiple factors and made the theory more applicable to empirical testing. While comparative advantage remains operative in this extension, Vanek showed that trade can be understood as occurring in factor services rather than directly in goods, a formulation known as the HOV model. This made the theory empirically tractable: rather than requiring detailed information about production functions and consumption patterns, researchers could test the model using observable data on factor endowments and trade flows. In essence, countries with a relative abundance of capital are expected to be net exporters of goods that embody large amounts of capital, that is, goods with a high capital "factor content". By focusing on the factor content of trade, the formulation by Vanek enabled researchers to assess whether countries export the services of their abundant factors simply by examining endowment data and measured trade flows.

When taken to data, the HO and the HOV model, however, failed due to their large number of assumptions (For example: (Leontief, 1953)). There has been a lot of literature that seeks to explain this difference and how it can be reconciled (Bowen et al., 1987; Davis & Weinstein, 2001; Trefler, 1993, 1995). Most recently, Trefler and Zhu (2010) showed that applying the factor content of trade formula by Vanek can be misleading when countries differ in production structures, in the efficiency of the factors, and when there is trade in intermediate inputs. They correct the factor-content predictions by accounting for these differences and make the HOV formulation far more applicable to technology-intensive and input-interconnected sectors.

An important implication of this literature is that not all factor endowments are fixed. Some factors, such as natural resources or geography, are inherited and largely exogenous. Others are formable and cumulative, shaped over time through investment, education, innovation, and policy (Leamer, 1984; Peneder, 2016). In periods of technological transformation, such as the current AI-driven transition, formable factors become especially important in shaping comparative advantage.

Within this context, the knowledge stock underpinning AI can be treated as a formable factor endowment. While technology is often viewed in Ricardian models as a residual in the production function rather than as a production factor, the HOV framework allows accumulated knowledge to be incorporated explicitly as a factor that is embodied in traded goods and services. Patents provide a natural proxy for this knowledge stock. They capture cumulative innovative activity, reflect country-level capabilities in frontier technologies, and shape competitive positions in global markets. Despite research establishing patents as a key measure of innovative capacity and output (Fleming et al., 2007; Griliches, 1990; Katila, 2000; Schilling & Phelps, 2007; Svensson, 2015; Tortoriello, 2015), current trade models have not used it, leaving a gap in our understanding of how patents can drive comparative advantage. This omission is particularly salient in the context of AI. Recent work shows that AI patents are increasingly distinct from broader ICT innovations (Cockburn et al., 2018), which merits splitting AI-related patent stock from the general patent stock, as it allows us to separate the impact of AI knowledge from broader innovative capacity. As AI diffuses across sectors and becomes more embedded in our lives, understanding whether AI-related knowledge stocks translate into trade advantages becomes essential.

This analytical perspective is particularly relevant for the EU. While the societal impact of AI ranges from harmless applications to sensitive uses such as facial recognition in policing, global responses have largely focused on either accelerating innovation, regulating risks, or both (Burnay & Circiumaru, 2023). The approach by China has been articulated in the 2017 New Generation Artificial Intelligence Development Plan, and subsequent policies align central planning, state-industry coordination, and regulatory tools that accelerate domestic capability to become the world leader in AI by 2030 (Creemers, 2025; Roberts et al., 2021). The US has been more innovation-first, relying on private stewardship to preserve technological leadership while developing targeted legal protections over time (Davtyan, 2025). The EU, on the other hand, has attempted to be a leader in ethical AI. It passed the first comprehensive AI law that proposes a risk-based regulatory framework banning certain AI uses, setting stricter rules for high-risk AI, and lighter rules for low-risk AI to leave room for innovation (European Commission, 2021).

While the prioritisation of ethical rules and digital sovereignty by the EU responds well to legitimate social and political priorities, it does not sit well against the fact that AI is a rapidly diffusing GPT whose creation and deployment are concentrated in a few firms and countries. This matters economically because if AI development and deployment remain concentrated abroad, then the EU risks falling behind not only in AI models but in the complementary assets as well, like data, specialised skills, and compute infrastructure - assets that determine who will have the most productivity gains from AI.

The report by (European Commission, 2025f) places innovation at the centre of strategic priorities for the EU, arguing that it must renew and coordinate its efforts to narrow the widening gap with both the US and China. Evidence from recent work by Veugelers (2024) supports this assessment: although the EU marginally outperforms the US in the number of AI-related academic publications, it falls well behind in terms of AI patents filed at the national level. This imbalance points to weaknesses in the innovation ecosystem of the EU and underlines the importance of developing a system that, in the words of the author, “encourages a wide pipeline of new ideas for commercialisation.” Concerns that Europe is losing ground at the technological frontier are not new and have been repeatedly documented in the literature (Cohen, 1992; Stöllinger & Landesmann, 2020; Stöllinger et al., 2013).

Building on this line of inquiry, recent empirical work has applied the factor-content adjustments introduced by Trefler and Zhu (2010) to show that countries with strong endowments in digital tasks and ICT capital tend to be net exporters of these factors (Stöllinger & Guarascio, 2023). Subsequent analysis finds that the US exhibits a higher intensity of digital tasks than the EU, a difference driven both by a greater concentration of digital-task-intensive occupations and by higher digital intensity within occupations themselves (Stöllinger & Guarascio, 2024). Taken together, these results strengthen the argument that the EU faces a structural disadvantage in AI-capabilities and risks further divergence from the global technological frontier.

To counter this, the EU recently came up with a roadmap for the "European way" to digitalisation through which it prioritised investing in digital skills, infrastructure, and AI regulations to achieve "technological sovereignty" (European Commission, 2020). Cantner (2023) defines technological sovereignty as an economy's ability to provide, further develop, standardise, and access critical technologies without one-sided technological dependencies. From this perspective, a lack of comparative advantage in AI-related knowledge implies declining technological sovereignty which may translate into technological dependence, increasing reliance on foreign AI inputs, models, and complementary assets that shape productivity growth and strategic autonomy.

Linking comparative advantage to technological sovereignty, therefore, requires an empirical assessment of whether AI knowledge endowments are reflected in trade patterns, and how the EU's position has evolved. If countries that are relatively abundant in AI patents are also net exporters of it, then comparative advantage becomes a meaningful channel through which technological leadership or dependence manifests in the global economy. On the other hand, a persistent deficit in AI-related factor content of trade would suggest structural vulnerabilities that must be addressed. This thesis thus contributes to the growing literature on the intersection of technological change and international trade by treating AI-related knowledge stocks, measured through patent data, as formable factors of production within an extended HOV framework.

This analysis is particularly relevant for the EU, given ongoing debates about technological sovereignty and the need to reduce dependencies on external suppliers of critical technologies (Caravella et al., 2024). The empirical findings shed light on whether the current endowments of the EU in AI-related knowledge are sufficient to support competitive positions or whether structural gaps exist that may require policy intervention. More broadly, the research demonstrates that patents can function as drivers of comparative advantage in much the same way as traditional factors such as capital and labour. This has implications not only for trade theory but also for innovation policy and the design of interventions aimed at strengthening national technological capabilities.

1.2. Research Objective and Questions

This thesis aims to analyse how the accumulation of AI-related knowledge has shaped the comparative advantage of countries in global trade since 2010, and to assess what the relative position of the EU implies for its ability to achieve and maintain technological sovereignty in the AI era. This is done by integrating AI-related patent stocks into an extended HOV framework using the factor-content corrections proposed by Trefler and Zhu (2010). In doing so, this thesis contributes to the HOV literature by incorporating AI-related patent stocks as a formable knowledge factor. It also connects empirical trade theory with the EU policy debate on technological sovereignty. To achieve this objective, the thesis looks to answer the following two-part research question:

How has the evolution of comparative advantage in AI since 2010 reshaped the global trade landscape? and what does the relative position of the EU imply for its ability to achieve technological sovereignty?

To address this question, this analysis incorporates four factor endowments:

1. AI-related patents (knowledge capital specific to AI)
2. Non-AI-related patents (general innovative capacity)
3. Labour
4. Capital

These factors are included for four reasons. First, they allow the calculation of the relative factor content of trade of AI-related patent endowments over non-AI-related patent endowments within an HOV framework. Second, they enable a ranking of countries' comparative advantage across different types of factor endowments, not just AI-specific knowledge. Third, they provide a plausibility check on the results by comparing AI-related patent endowments with more traditional factors, which previous literature has worked immensely on. Fourth, they allow an assessment of whether AI patents perform differently from other traditional innovation-related endowments, namely, labour and capital, in explaining trade patterns.

Using these four factors, this thesis aims to address the following five research sub-questions, to answer the main research question above:

RQ1

What are the patterns of AI and non-AI patent stocks across countries in the EU and its main trading partners, 2010 onwards?

This question tries to document the concentration and the relative growth of AI-related and non-AI-related patent stocks across countries. By constructing patent stock measures from patent flows, the analysis provides descriptive evidence on whether AI knowledge accumulation is becoming more concentrated and whether the EU is losing ground relative to the US and China. This will be presented using descriptive statistics and visual trends (levels, growth rates, shares), mapping geographic and sectoral patterns. Establishing these patterns is a necessary first step, as comparative advantage cannot be meaningfully analysed without understanding the underlying distribution of knowledge endowments.

RQ2

To what extent do the AI patent stock endowments of countries predict their trade patterns according to the HOV framework?

This question tests the core theoretical mechanism of the thesis. Using the factor content methodology proposed by Trefler and Zhu (2010), the factor content of net exports is computed for all four endowments. Predicted factor contents from the HOV framework and measured factor contents from the Trefler and Zhu (2010) methodology are then compared using sign and rank tests used by Leamer (1980). This allows an assessment of whether AI-related patent abundance is systematically associated with net exports of the factor content, and whether AI patents perform better or worse than other factors in explaining trade patterns. This helps establish the link between formable knowledge endowments (patents) and comparative advantage in the AI GPT-era.

RQ3

Which countries hold the comparative advantage in AI patents as of the most recent data?

Building on the factor-content results, this question calculates the relative factor abundance of AI patents over non-AI patents between all countries and ranks them by AI patent comparative advantage. The goal is not only to see the ranking but also the difference in magnitude between the countries. This further analysis of the empirical test to generate the rankings will help confirm if the concentration of AI capabilities is split between the US and China or if there are more countries involved. It will also help identify which countries supply the AI knowledge capital that the EU may rely on or compete with, and provide insight into the structure of global AI dependence and competition.

RQ4

How has the comparative advantage in AI patents of countries in the EU and its main trading partners changed since 2010?

This question analyses the changes in relative factor abundance and factor content of trade over time. These are analysed particularly in the context of the EU to see if the position has improved, stagnated, or deteriorated relative to the US, China, and other major trading partners. This helps contribute to the literature of the EU falling behind the technological frontier, and the risk that it could fall further behind unless the formable factors for innovation are actively built.

RQ5

What are the implications of the distribution of comparative advantage in AI patents for the digital sovereignty strategies of the EU?

This question serves as the bridge between empirical findings and policy relevance. It interprets the empirical insights from the previous sub-questions in light of the literature on technological sovereignty, technological dependence, and open strategy autonomy and helps draw policy-relevant implications for the EU.

1.3. Relevance to Management of Technology (MOT)

This thesis addresses a question that is central to the MOT program: How can countries measure their competitive positions in emerging technological paradigms like AI? It studies how the technological knowledge a country has built over time affects its competitive position in global markets and uses a multi-disciplinary approach that connects technology, international trade, and public policy.

The thesis demonstrates key competencies taught in the MOT program. It treats technology as a factor that can be shaped and that contributes to productivity and comparative advantage. The MOT curriculum stresses that technology management requires understanding not just the technical aspects but also the strategic choices firms and countries face regarding innovation, commercialisation, and resource allocation. This thesis operationalises that principle by treating AI-related knowledge stocks as a strategic resource whose abundance or scarcity determines which nations can export the AI-intensive goods and services that will shape future economic growth.

The research draws on several theoretical frameworks covered in the MOT curriculum, including GPTs, the diffusion patterns of technology, different industrial policies for breakthrough innovations, and the role of factor endowments in international trade. By linking AI-related comparative advantage to technological sovereignty, the thesis connects international trade outcomes with macroeconomic and industrial policy. It shows how patent-based measures of knowledge can help measure economy-wide outcomes that influence national competitiveness.

The study also speaks directly to current policy and strategic decisions. The EU policymakers and technology managers face a concrete problem: Should Europe invest heavily in building AI capabilities domestically, or can it rely on imports of AI-enabled goods and services from the US and China? The thesis aims to provide empirical evidence that comparative advantage driven by AI knowledge stocks shapes trade patterns, offering a data-grounded framework for evaluating whether EU technological sovereignty strategies are aligned with underlying economic realities. Understanding the magnitude of disadvantage in AI-related patent endowments for the EU and how this translates into trade dependencies helps managers and policymakers make more informed decisions about innovation investment, regulatory frameworks, and strategic partnerships. In this way, the research contributes to the goal of the MOT program to educate managers to navigate the complex intersection of technology, markets, and policy to sustain national competitiveness and enable transformative change.

1.4. Thesis Outline

This thesis is structured in seven chapters. Chapter 1 introduces the research topic, highlights the problem context, and outlines the research objectives and questions. Chapter 2 reviews the relevant literature on trade theory, the HOV framework, and recent applications to knowledge-intensive factors. It also situates the research within the broader debate on technological sovereignty and EU competitiveness. Chapter 3 provides a detailed account of the research methodology and the data sources used in the empirical analysis. Chapter 4 presents descriptive findings on the distribution of AI-related and non-AI-related patent stocks across countries and industries, addressing the first research question. Chapter 5 reports the empirical results from tests of the HOV framework and examines patterns of comparative advantage in AI knowledge, addressing research questions two through four. Chapter 6 integrates these empirical insights with the literature on technological sovereignty, technological dependence, and open strategic autonomy and derives policy implications for the EU in answer to the fifth research question. Chapter 7 concludes by summarising the main findings, discussing the contributions and limitations of the study, suggesting directions for future research, and a personal reflection on the thesis journey. Table 1.1 summarises this outline.

Table 1.1: Thesis Outline

Chapter	Description
1. Introduction	Research topic, Problem context, Research objectives, Research questions
2. Literature Review	Key concepts definition, Relevant Literature review, Gaps in existing research
3. Methodology and Data	Research design and methodology, Data choices along with justification
4. Descriptive Results of Factors	Findings from the descriptive analysis of factors
5. Empirical Results	Empirical results and findings
6. Implications	Empirical insights integration with the literature on technological sovereignty and open strategic autonomy, Policy implications for the EU
7. Conclusion and Discussion	Conclusion to the main research question, Key limitations discussion, Future research directions, Reflection on thesis journey

2

Literature Review

This chapter reviews the theoretical foundations and literature that underpin the analysis of this thesis. The review has been kept concise and focused on establishing core concepts, with more detailed engagement with specific literatures integrated into subsequent chapters where their connection to the empirical analysis is most direct.

First, the review examines the core principles of international trade theory, with emphasis on the HO model and its factor content extension developed by Vanek (1968). The mathematical formulation and operational details of the HOV framework and its extension by Trefler and Zhu (2010) are discussed further in Chapter 3.1, where the empirical implementation of this study is presented. Second, the review discusses the literature on testing and refining the HOV framework, with attention to recent applications. The operational details of the HOV tests and calculation of relative factor abundance for comparative advantage are similarly discussed further in Chapters 3.9 and 3.10 respectively. Third, the review briefly discussed the literature on patents as measures of innovative capacity with further discussion on patent based measures integrated into Chapter 3.4, where the empirical context for patent stock construction is established. Finally, the literature on technological sovereignty, technological dependencies, open strategic autonomy, and the European Paradox is reviewed to provide the framework for interpreting the empirical findings. This is explored more deeply in Section 6.1, where these theories are applied to interpret the descriptive and empirical results.

2.1. Related Literature

This study is grounded in the HO theory of international trade, which accounts for trade patterns through cross-country differences in relative factor endowments (Heckscher, 1919; Ohlin, 1924). In contrast to Ricardian models, where comparative advantage arises from exogenous technological differences (Ricardo, 1817), the HO framework is explicitly centred on endowments, positing that countries tend to export goods that make intensive use of the production factors they possess in relative abundance.

In its most basic formulation, the model implies that economies rich in labour will specialise in labour-intensive goods, whereas economies with abundant capital will specialise in capital-intensive goods. For example, a labour-abundant economy, such as India, would be expected to specialise in and export labour-intensive products, such as textiles. In this way, the HO model offers a clear endowment-based rationale for observed patterns of comparative advantage in global trade.

Underlying this mechanism is the broader concept of comparative advantage that features prominently across modern trade theory and is defined in relative rather than absolute terms. A country may be more productive across all sectors and still benefit from trade by specialising in activities where its relative efficiency advantage is strongest. The HO model formalises this insight by tying comparative advantage to relative factor abundance, as opposed to differences in absolute productivity levels.

The classical HO framework relies on several strong assumptions. The important ones are that technologies are identical across countries, factors of production are mobile within a country but immobile outside, countries share homothetic preferences (increase in income results in proportional increase in all goods), markets are perfectly competitive, and production functions give constant returns to scale (if you increase all of your inputs to the production function by a certain percentage, the output will increase by the same percentage). Under these conditions, differences in relative factor endowments alone determine trade patterns. While these assumptions facilitate analytical clarity, they also limit the model's empirical applicability.

To bring the HO model closer to empirical testing, Vanek (1968) extended this model into the factor-content framework. He expresses trade not in terms of goods directly, but factors embodied in those goods. Instead of saying, "A capital-abundant country exports machines" you can say, "A capital-abundant country exports capital through goods and services containing it".

The key intuition of the HOV model is that a country's net exports should embody the factors in which it is relatively abundant, after accounting for its share in world consumption. If a country is relatively abundant in a given factor, it should be a net exporter of that factor in embodied terms. This insight made the HO theory empirically testable by linking observed endowments to the measured factor content of trade.

However, empirical work testing the HO and the HOV model yielded disappointing results initially. The most famous test was by Leontief (1953), who studied US trade data. According to the HO model, the US, being capital-abundant at the time, should have been exporting capital-intensive goods and importing labour-intensive goods. Leontief (1953), however, found the opposite. This came to be known as the "Leontief Paradox". One way to understand the paradox is to think about the US labour market. Even though the US had fewer workers, its workers were more productive due to higher education and skills. The "effective labour" of the US, thus, may have been relatively abundant, a nuance that was not captured by the HO framework.

A substantial body of literature emerged in the 20th century to explain this paradox and to reconcile theory with data. Leamer (1980) argued that Leontief had performed the wrong empirical test. Rather than comparing the factor intensity of exports and imports, relative factor abundance should be assessed by comparing factor use in production with factor use in consumption. Using sign and rank tests consistent with the HOV framework, he showed that the U.S. could still be classified as capital-abundant.

Bowen et al. (1987) conducted one of the first large-scale empirical tests of the HOV model across multiple countries and factors. Using sign and rank tests, they compared the measured factor content of trade, derived from trade and input–output data, with the predicted factor content, derived from countries' endowments and consumption shares. They found that the model performed poorly in many cases, with failures largely attributable to the restrictive assumptions.

Subsequent research focused on relaxing these assumptions. Trefler (1993) showed that allowing for cross-country productivity differences could explain much of the discrepancy between predicted and observed factor content trade. Imagine two countries that both have lots of capital. Country A uses capital with more advanced machines (more productive), while Country B uses the same amount of capital but is less productive. Even if endowments of these two countries look similar, the effective factor, i.e., capital x productivity, differs, and therefore trade patterns and factor prices differ.

Trefler (1995) subsequently documented the "missing trade" puzzle, i.e., standard HOV predictions implying much more factor of content trade than is actually measured. He used factor requirement matrices to capture the cross-country technology differences as opposed to calculating the effective factor endowments. This helped in reducing a significant part of the "missing trade". He further investigated explanations like non-tradable goods, trade costs, and home-market bias, and showed that productivity differences explain a big part of it, but not all of it.

Davis and Weinstein (2001) further demonstrated that once the HOV model was made more realistic by recognising that countries can use different technologies, some goods are not traded internationally, wages and returns to capital are not equal across countries, and moving goods across borders involves costs, then the predictions line up much better with real trade patterns. These findings reinforced the relevance of the factor-content approach while highlighting the need for empirically grounded extensions.

Building on the insight that technology differences matter, Hakura (2001) explicitly relaxed the assumption of identical production techniques across countries. She proposes a bilateral formulation in which relative factor abundance and the associated factor content of trade are calculated on a pair-wise basis, using each pair of countries' own technology coefficients. By introducing this bilateral perspective, she shows that accounting for technology variation improves the alignment between predicted and observed factor contents, highlighting the importance of allowing technology heterogeneity in empirical tests of factor-based trade theories.

Debaere (2003) subsequently refined the concept of relative factor abundance by emphasising its inherently comparative nature. A country is relatively abundant in one factor compared to another only if its factor ratio exceeds that of another country. This clarification strengthened the conceptual foundation of empirical HOV testing.

Trefler and Zhu (2010) addressed a central shortcoming in the empirical HOV literature by clarifying how the Vanek prediction should be formulated once key real-world features are taken into account. In particular, they asked how the prediction changes when countries differ in production technologies and when traded goods are used as intermediate inputs in the production of other goods. Their analysis yielded a precise and operational definition of the factor content of trade that could be applied directly to the data. In addition, they introduced a "consumption-similarity" condition, which they showed to be both necessary and sufficient for the Vanek prediction to hold (Trefler & Zhu, 2010).

This contribution represented a major advance for empirical work in the area. It coincided with improvements in the construction of International Input Output (IIO) tables and provided researchers with a clear algebraic framework and testable implications, thereby reducing ambiguity about what should be measured in applied settings. The use of IIO tables also allowed productivity differences across countries to be incorporated while simultaneously accounting for trade in intermediate inputs. As a result, the empirical relevance of the HOV model was substantially enhanced, particularly in contexts characterised by technology-intensive production and globally fragmented value chains.

Stehrer (2014) takes the insight from Trefler and Zhu (2010) and pushes it further into the demand side. He uses the modern World Input Output Data (WIOD) and allows for three real-world features of consumption. He allows for non-homothetic preferences (with a change in income consumption share on goods changes), home bias (people in a country tend to consume a larger share of goods that are produced at home), and geographic sourcing patterns (trade flows depend on distance). Accounting for this solves the "missing trade" problem, and the predicted and measured factor contents match much better.

There has also been research adding complementary empirical perspectives to the factor-content literature. For example, Bernhofen and Brown (2005) asked how big the welfare gains were from opening trade with comparative advantage as the driver? They used the 19th-century forced opening of Japan for this investigation. In the 1850s, Japan could not import cheap rice, cotton, or capital goods. After opening, resources were reallocated to sectors where Japan had a comparative advantage, and consumption possibilities expanded, which the authors quantify.

More recent contributions to the literature used the HOV formulation to explore comparative advantage in technology, notably ICT and digital technologies. Chor (2010) builds a model to decompose sources of comparative advantage and explicitly isolates ICT capital as a distinct channel. Wang and Li (2017) show that ICT helps exports, but its effect is strongest for R&D or task-complex industries. Stöllinger and Guarascio (2023) treat digital tasks and ICT capital as HOV factors and find that countries tend to export the digital factors they are abundant in (HOV passes the sign and rank tests reasonably well in the EU sample). Stöllinger and Guarascio (2024) then compare the EU with the US and shows that the US is more digital-task abundant, helping explain US digital leadership.

Despite these advances, two important gaps remain. First, much of the recent work focuses primarily on the EU and the US, omitting key global competitors such as China. Second, while digital technologies have been studied, knowledge endowments, and more specifically, AI-specific knowledge endowments, have not yet been integrated into the HOV framework. Empirical research has been done on developing new measures to measure the exposure of occupations to AI (Felten et al., 2018), but the focus has been more on the labour market impacts rather than international trade implications. While recent work has examined determinants of comparative advantage in AI-intensive industries (Bonfiglioli et al., 2025), no study has utilised any of the earlier-mentioned extended HOV models for AI patent endowments.

AI patents serve as a relevant factor endowment for countries to measure comparative advantage in AI, as they reflect the innovative capacity and technological expertise of a nation. Research has shown that patent applications can effectively indicate innovation and technological advancement (Burhan et al., 2017). This is supported by the latest AI index, which states that between 2010 and 2023, the number of AI patents ballooned from 3,833 to 122,511 (Maslej et al., 2025). Soete (1987) further emphasises that innovation plays a crucial role in shaping international trade patterns, suggesting that countries with technological advancements can develop a comparative advantage. This aligns with the notion that AI patents can serve as a technological capability indicator of a country and, by extension, its comparative advantage in AI.

Against this background, one of the key objectives of this research is to analyse AI patent endowments in the EU and its main trading partners, including the U.S. and China, and to assess how these endowments translate into comparative advantage in trade. The investigation of this question, while always relevant, has become virulent with recent geopolitical tensions and concern about excessive technological dependence.

Recent research has highlighted the growing dependence of Europe on foreign suppliers for critical technologies and components. Guarascio et al. (2025) document how Europe has become dependent on a few key suppliers, particularly China, for critical components, creating vulnerabilities that extend beyond economic concerns to encompass strategic risks. Reiner and Stöllinger (2025) present a more urgent case, arguing that Europe must regain technological sovereignty or risk losing global relevance in an increasingly competitive technological landscape.

The intensification of technological competition between the US and China has fundamentally reshaped the global innovation environment. Zúñiga et al. (2024) and Calcara et al. (2025) show that this competition extends beyond trade disputes to encompass control over critical technologies, standard-setting processes, and the configuration of global value chains. The EU finds itself positioned between these two technological superpowers, functioning both as a "playground" where American and Chinese ambitions intersect and as a "player" capable of acting independently in shaping technological outcomes (Calcara et al., 2025).

The COVID-19 pandemic and invasion of Ukraine by Russia exposed the extent of technological dependencies in the EU, particularly in semiconductors, cloud computing, and digital infrastructure (Guarascio et al., 2025). These events caused a shift in European perceptions. It started recognising the security risks associated with technological interdependence and adopted a tripartite definition of China as simultaneously a partner to cooperate with, a competitor pursuing leadership in technology, and a rival that is promoting alternative models of governance that the EU does not align with (Brown, 2024).

In this context, technological sovereignty emerged as a central concept in European policy discussion. Edler et al. (2023) define technological sovereignty as the capacity of a country to provide secure access to technologies it considers important for its economy, security, and autonomy. This means being able to either develop the technologies domestically or obtain them from diverse external sources, without being structurally dependent on any single foreign power. Cantner (2023) further operationalises this concept by distinguishing between "mastery" (domestic knowledge and capabilities) and "availability" (secure access to foreign technology), arguing that countries lacking both dimensions face vulnerabilities including higher prices, supply disruptions, and weak bargaining power.

Technology-gap trade models, discussed by Cantner (2023), predict specific dynamics for economies that specialise in older technologies while importing advanced ones. First, technology gaps widen as leaders experience cumulative learning effects in new domains. Second, terms of trade deteriorate as countries import key technologies at rising relative prices while exporting goods in slower-growing sectors. Third, domestic mastery progressively erodes because industries cannot build sufficient absorptive capacity when high-end capabilities are externalised. Importantly, Cantner (2023) notes that economies specialising in "old" technologies tend to reinforce this pattern unless they deliberately invest in new general-purpose technologies with high learning potential, even when this contradicts existing comparative advantage.

The concept of technological sovereignty connects directly to broader debates about open strategic autonomy and economic security. Fabry and Veskoukis (2021) describe open strategic autonomy as a middle ground between free-market openness and protectionism, where open trade is combined with targeted tools to manage critical dependencies and strengthen resilience. Dupré (2022) conceptualises it as functioning both as a "backbone" and an "immune system," aiming to protect Europe from harmful external dependencies without pushing toward isolation or autarky.

The European Commission has attempted to improve technological sovereignty and open strategic autonomy through initiatives aimed at shaping the digital future of

Europe while preserving what it calls the "European way" (European Commission, 2020). The proposed AI Act represents the most comprehensive attempt to establish regulatory frameworks that balance innovation with ethical considerations and fundamental rights (European Commission, 2021). Ulnicane (2022) mentions how EU institutions have framed AI as both a transformative technology and a field of intense global competition. Since the 2018 AI Communication, the EU strategy has pursued multiple goals simultaneously: boosting technological capacity, managing social and economic change, and building an ethical and legal framework rooted in fundamental rights. This results in what Ulnicane (2022) characterises as a hybrid strategy combining "Normative Power Europe" (shaping global standards through regulation) and "Market Power Europe" (leveraging the large internal market).

However, the effectiveness of regulatory approaches in achieving technological sovereignty and open strategic autonomy depends critically on underlying technological capabilities. Caravella et al. (2024) document increasing dependence of Europe on a small set of foreign suppliers for critical inputs like semiconductors and hardware. This raises questions over the current policy approaches and highlights the challenge outlined in open strategic autonomy literature, i.e., determining which technological capabilities are truly critical and developing strategies to either develop them domestically or secure them through diversified international partnerships.

Despite concerns about technological capabilities, several studies indicate that science base of Europe remains comparatively strong. Veugelers (2024) demonstrates that the EU continues to lead in AI-related publications, though this lead is shrinking as China expands its scientific output. European Commission et al. (2024) conclude that Europe hosts a large, diversified scientific community and maintains strong capabilities across many scientific domains. The report by European Commission (2025f) emphasises that the fundamental challenge of Europe lies in translating excellent science into commercial innovation and scale-ups rather than in the quality of the research base itself.

This pattern recalls what Dosi et al. (2006) termed the European Paradox: the disconnect between the strong scientific performance of Europe and its weaker record in translating that science into technological and commercial success. Dosi et al. (2006) argue that this paradox reflects structural features of European innovation systems, including fragmentation across national borders, insufficient risk capital, and institutional barriers to knowledge commercialisation. The persistence of this paradox raises questions about whether scientific strength alone can provide the foundation for technological sovereignty, or whether fundamental changes in the innovation-to-commercialisation pipeline are required.

This thesis contributes to the literature in three ways. First, it integrates AI-specific knowledge stocks, measured through patent data, as a distinct factor endowment within the extended HOV framework developed by Trefler and Zhu (2010), addressing the gap identified where knowledge endowments, and AI-related knowledge in particular, have not yet been incorporated into factor content analysis. By distinguishing AI-related patents from broader innovative capacity, the research recognises AI as an emerging GPT with distinct characteristics that warrant separate treatment from general ICT or patent stocks. Second, it broadens the geographic scope of recent HOV applications to include China alongside the EU and US, enabling a comprehensive assessment of comparative advantage patterns among all three major technological powers which shape the global AI landscape. Third, it links empirical measures of comparative advantage in AI knowledge to the literature on technological sovereignty, technological dependencies, open strategic autonomy, and the European Paradox, providing an analytical foundation for evaluating whether the regulatory leadership of Europe in AI is supported by underlying technological capabilities or whether structural gaps exist that policy interventions must address.

3

Methodology and Data

This chapter presents the methodological framework and data sources used to examine the role of AI-related knowledge in shaping countries' comparative advantage in international trade. The chapter is structured to provide both conceptual clarity and operational detail for the empirical implementation.

Section 3.1 establishes the theoretical foundation by outlining the HOV framework and explaining how the four-factor model (AI-related patents, non-AI-related patents, labour, and capital) is operationalised using the approach by Trefler and Zhu (2010). Section 3.2 justifies the sample selection and addresses the key data requirements. Section 3.3 outlines the empirical strategy, describing how the research questions are addressed through sequential stages of analysis. Sections 3.4 through 3.6 describe the construction of each factor endowment measure in detail, explaining data sources, measurement challenges, and the procedures used to ensure consistency across countries and industries. Section 3.7 demonstrates how these components are combined to calculate the measured factor content of trade, while Section 3.8 explains the construction of predicted factor content based on the classical HOV framework. Section 3.9 outlines the statistical tests used to evaluate the empirical validity of the HOV model, and Section 3.10 describes how comparative advantage rankings are derived from factor endowments and measured factor content. Finally, Section 3.11 presents robustness checks and sensitivity analyses designed to assess whether the empirical findings are stable across alternative specifications and data choices.

3.1. Theoretical Foundation

This thesis examines the role of accumulated AI-related knowledge in shaping countries' comparative advantage in international trade since 2010, with a particular emphasis on the EU's relative position and the implications for its technological sovereignty goals. To pursue this objective, the analysis embeds AI-related patent stocks, non-AI-related patent stocks, labour, and capital stock within an extended HOV framework, drawing on the factor-content corrections developed by Trefler and Zhu (2010).

The empirical strategy follows directly from the HOV literature reviewed in Chapter 2. In its classical form, the HOV model predicts that a country's net exports should embody the factors in which it is relatively well endowed, once its share of global consumption is taken into account. In this thesis, this implication is referred to as the predicted factor content of trade and is formally represented by the Vanek (1968) equation:

$$\tilde{F}^c = V^c - \sigma^c \cdot V^W \tag{3.1}$$

Here, V^c and V^W denote the vectors of factor endowments for country c and the world, respectively, while σ^c captures country c's share of world consumption. Under the standard assumptions of the classical HOV framework, most notably identical technologies across countries and homothetic preferences, the predicted factor content $\tilde{F}^c$ is expected to correspond closely to the factor content observed in actual trade flows.

As reviewed in Chapter 2, empirical tests of this baseline specification performed poorly, motivating a series of extensions aimed at relaxing its restrictive assumptions. The most significant advancement in the HOV model was made by Trefler and Zhu (2010), who explicitly incorporate cross-country technological differences and trade in intermediate inputs. Using IIO tables, they propose a method for measuring the factor content of trade for a given country, denoted by f^c, based on inter-country and inter-industry trade relationships and three key components. The first is the vector of factor inputs per unit of gross output, e, which indicates, for example, the amount of labour required to produce one unit of output and has dimension $C \cdot I \times 1$, where C denotes the number of countries and I the number of industries. The second component is the global Leontief inverse, L, a matrix of dimension $C \cdot I \times C \cdot I$ that summarises both direct and indirect input–output relationships across countries and industries, capturing the total output required throughout the production network to satisfy a unit of final demand. The third element is the country-specific net trade vector, T^c, which records the total exports and bilateral imports for each country-industry and also has dimension $C \cdot I \times 1$. Following Trefler and Zhu (2010), the factor content of country c's net exports for factor f is computed as:

$$f^c = e' \cdot L \cdot T^c \tag{3.2}$$

By post-multiplying the net trade vector T^c with the global Leontief inverse L, this formulation incorporates both the direct and indirect use of intermediate inputs embodied in traded goods. Pre-multiplication by the factor input vector e' then converts gross output requirements into factor requirements, while accounting for productivity differences across countries. The resulting measure captures the number of "productivity-equivalent" units of a given factor embodied in a country's net exports. This approach enables the analysis to trace indirect flows of AI technologies through complex global value chains and to reflect cross-country differences in AI-related productivity and capabilities. In our analysis, this measure is referred to as the measured factor content of trade.

3.2. Sample Selection and Data Requirements

The empirical implementation requires IIO data capturing the full structure of inter-country and inter-industry production linkages. For this research, the 2025 edition of the FIGARO database by Eurostat is utilised (Eurostat, 2025). FIGARO provides comprehensive input-output tables for 27 EU countries, 18 main trading partners of the EU, and a rest-of-world aggregate, covering 64 industries classified according to NACE Revision 2 for the period 2010 to 2021. Importantly, FIGARO captures trade flows in both goods and services. Specific service industries represented in FIGARO include J62_63 (Computer programming, consultancy, and information service activities), which is particularly relevant for AI as it is increasingly diffusing through these services.

This sample of 45 countries plus a rest-of-world aggregate was selected to address specific gaps identified in the literature while ensuring data quality and consistency. First, as noted in Chapter 2, recent factor-content studies have focused primarily on the EU and the US, omitting key global competitors such as China. Including China in the analysis is essential given its rapid emergence as a major innovator in emerging technologies and the geopolitical significance of US-China-EU technological competition discussed by Zúñiga et al. (2024) and Calcara et al. (2025). Second, from a European policy perspective, coverage of the main trading partners of the EU is necessary to identify potential dependencies in imports of goods and services embodying AI patents. Third, the analysis requires the most recent input-output data available to capture the contemporary structure of production linkages. Given these requirements, FIGARO emerged as the most suitable database. While other databases exist, such as the OECD Inter-Country Input-Output (ICIO) database or the WIOD, FIGARO offers a better combination of country coverage, industry detail, and data through 2023, which is particularly valuable as this period captures the rapid diffusion of AI technologies documented by Maslej et al. (2025).

The FIGARO IIO tables provide the components needed for constructing the global Leontief inverse L and the net trade vectors T^c. To complete the calculation of measured factor content using equation 3.2, the factor requirements matrix e' must be constructed, which requires data on four factors: AI-related patent stocks, non-AI-related patent stocks, labour, and capital stock. The construction of each of these factor measures is described in detail in the subsequent sections.

3.3. Empirical Strategy

The empirical analysis proceeds in stages corresponding to the research sub-questions outlined in Chapter 1.2. First, a descriptive analysis of AI and non-AI patent stocks across countries is conducted to understand whether certain countries, particularly the US and China, are building dominant positions in AI-related knowledge and to assess the relative position of the EU (RQ 1).

Second, the analysis tests whether AI patent stock endowments of countries predict their trade patterns according to the HOV framework by comparing the predicted factor content calculated using Equation 3.1 with the measured factor content calculated using Equation 3.2. Following Leamer (1980), both sign and rank tests are used alongside regression analysis to assess alignment between predictions and observations (RQ 2).

Third, the measured factor content results are used to identify which countries hold a comparative advantage in AI-related patents as of the most recent complete and valid data. This involves calculating relative factor abundance following Leamer (1980), who demonstrated that a country is relatively abundant in a factor if the ratio of that factor to another factor in production exceeds the corresponding ratio in consumption (RQ 3).

Fourth, the evolution of comparative advantage in AI patents 2010 onwards is analysed to identify trends and assess whether the position of the EU has improved, stagnated, or deteriorated relative to major competitors (RQ 4).

Finally, the empirical findings are interpreted in light of the literature on technological sovereignty, technological dependence, open strategic autonomy, and the European paradox to draw policy-relevant implications for the EU (RQ 5). This synthesis connects the quantitative results on comparative advantage with broader strategic questions about the ability of Europe to achieve and maintain technological leadership in the AI era.

3.4. Measuring Patent Stocks

Patent data serve as the primary measure of AI-related and non-AI-related knowledge endowments in this research. While patents have some limitations as innovation indicators, i.e., not all innovations are patented and not all patents have equal value, they remain the most comprehensive and internationally comparable measure of technological knowledge available. The research literature has extensively validated patents as indicators of innovative capacity and output.

For this research, the WIPO PATENTSCOPE database is used, which provides access to patent applications filed at national patent offices and Patent Cooperation Treaty (PCT) applications filed at WIPO (World Intellectual Property Organization, 2025b). The database offers multiple filtering options, including country, year, International Patent Classification (IPC) codes, patent titles, and patent front pages, along with translated patent content in English. Importantly for this research, WIPO recently published an AI Index that provides specific queries to identify patents related to AI. This allows separating AI-related patents from the broader patent applications (World Intellectual Property Organization, 2025a).

However, constructing suitable patent stock measures for use in the HOV framework requires addressing several methodological challenges. First, an appropriate patent indicator must be selected that balances quality and coverage while minimising biases toward particular countries or patent systems. Second, the dates and address references to use for assigning patents to countries and time periods must be determined. Third, patents, which are classified by technology codes, must be mapped to industries as defined in the IIO tables. Fourth, patent flows need to be converted into patent stocks that reflect the accumulated knowledge capital available in each period. Each of these challenges is addressed systematically below.

3.4.1. Choice of a Patent Indicator

The patent manual by OECD (2009) draws attention to several limitations inherent in patent data sourced from a single national patent office. A key issue is the presence of a strong "home advantage" effect, whereby domestic applicants file a disproportionately large share of patents in their own country relative to foreign applicants. This pattern reflects both the priority inventors place on securing protection in their home market and their greater familiarity with domestic legal and administrative procedures. Relying exclusively on data from a single office, such as the United States Patent and Trademark Office (USPTO), would therefore risk overstating the innovative output of domestic applicants while underrepresenting the activity of foreign inventors who may not seek protection in that jurisdiction for all of their inventions.

Two commonly used patent indicators are considerably less affected by this source of bias: patent families and PCT applications. Patent families group together patent filings made in multiple jurisdictions that are linked by one or more priority applications and correspond to the same underlying invention. The most widely employed definition is the triadic patent family, which includes applications filed at the European Patent Office (EPO) and the Japan Patent Office (JPO) and patents granted by the USPTO. Because inclusion requires protection to be sought in several major markets, patent families mitigate home bias and implicitly apply a quality filter. However, the PATENTSCOPE database does not offer direct access to patent family information, while alternative sources such as the Organisation for Economic Co-operation and Development (OECD) patent database provide only aggregated country-level indicators, which lack the industry-level detail required for this study.

By contrast, PATENTSCOPE offers comprehensive information on PCT applications filed with WIPO. PCT filings can be interpreted as quasi-global patent applications and are substantially less biased than data drawn from individual national offices. As documented by OECD (2009), use of the PCT system has increased steadily across member countries and provides broad coverage, including for developing economies, from the early 2000s onwards. The PCT process consists of two stages. The initial international phase is relatively low-cost and is typically used when applicants believe an invention has potential value beyond the domestic market. The subsequent national phase entails higher costs and reflects the decision to pursue patent protection in one or more national jurisdictions. Although PCT applications are not equivalent to granted patents, the financial commitment involved exceeds that of a purely domestic filing, implying that PCT applications signal inventions with meaningful expected commercial value.

OECD (2009) recommends focusing on PCT applications that have entered the national phase, as these represent cases where applicants have taken concrete steps toward obtaining enforceable patent rights. A drawback of this approach is the associated time lag. It can take up to 31 months from the initial filing for a PCT application to reach the national phase. To balance data quality and coverage, this study collects PCT applications that have entered the national phase in at least one patent office. As a consequence, the analysis period is limited to 2021, since more recent filings may not yet be fully updated with national-phase entry information. As a robustness check, an alternative dataset including all PCT applications, both those still in the international phase and those that have entered the national phase, is also collected to assess whether this choice affects the results.

It should be acknowledged that PCT-based measures are not entirely free from bias. The use of the PCT system varies across countries due to differences in legal frameworks, economic considerations, and the fact that the system is particularly attractive for inventions with clear international commercial potential. Nonetheless, PCT applications that have entered the national phase constitute a substantially more balanced and quality-filtered indicator of innovative activity than patent data from any single national office. To increase transparency regarding remaining sources of bias, a preliminary analysis compares patent filings and grants at the five largest patent offices worldwide with the number of PCT applications filed. This comparison is reported in Appendix B and provides insight into how the choice of patent indicator may influence the empirical results.

3.4.2. Patent Indicator Limitations

Two important limitations of the patent data must be acknowledged. First, in this analysis, all patents are weighted equally, although their technological and economic value varies enormously in practice. As emphasised by Schankerman and Pakes (1986), patent values are skewed, with a smaller section of patents accounting for the majority of economic returns. Ideally, one would use citation-weighted patent counts or other quality metrics to account for these differences, as breakthrough innovations and incremental improvements should not be treated as equivalent. However, the WIPO PATENTSCOPE database does not provide citation data with the geographic and temporal coverage required for this analysis. Given this constraint, this thesis uses unweighted patent counts, acknowledging that this approach treats all patents as equivalent contributions to knowledge stocks. Future research with access to more comprehensive quality-adjusted patent data would provide a valuable extension to the findings presented here.

Second, the empirical analysis in this thesis is based on data covering the period 2010 to 2021. It is important to acknowledge that this timeframe concludes before the generative AI explosion that began with the public release of ChatGPT in November 2022. This limitation warrants careful consideration, as the post-2022 period has witnessed unprecedented acceleration in AI capability, commercialisation, and public attention. However, work on AI was already progressing rapidly well before the emergence of generative AI. Governments had begun formulating AI strategies and investing in AI development as early as 2014, as documented by Maslej et al. (2025). The knowledge stocks captured in this analysis, therefore, reflect the accumulated innovative efforts that laid the groundwork for the current AI landscape. While the data do not capture the most recent developments in generative AI, they do capture which countries had already shifted focus toward AI development and were actively building in this domain. The findings thus provide a baseline understanding of the distribution of AI capabilities before the generative AI wave and offer insights into which countries were positioned to benefit from subsequent technological advances.

3.4.3. Reference Date

Each patent document contains several important dates that could be used for temporal assignment. The priority date corresponds to the first time a patent application is filed anywhere in the world and most closely approximates the date of invention. The application date is when the PCT application is filed at WIPO. The publication date, typically 18 months after the priority date, is when the invention is made available to the general public. The grant date is when patent rights are formally conferred by the authorised patent office.

OECD (2009) recommends using the priority date for compiling patent statistics because it best reflects the timing of the inventive activity. However, the PATENTSCOPE database provides only the application date in the downloadable data files, which limits our options. To assess whether this limitation introduces significant distortions, the distribution of PCT applications was compared across countries and years using priority dates versus application dates in the OECD patent database. The differences were found to be negligible and uniform across countries, suggesting that using application dates instead of priority dates does not materially affect the results. Therefore, all patent counts in this research are assigned to years based on the PCT application date.

3.4.4. Reference Country

For geographic assignment, patent documents can be assigned to countries using several alternative address indicators, each capturing a distinct dimension of innovative activity. The applicant's country of residence reflects the ownership and economic control of the invention and is commonly interpreted as an indicator of the innovative performance of a country's firms. The inventor's country of residence, typically corresponding to the professional address, captures the location of inventive effort and the contribution of domestic laboratories and human capital. The priority office refers to the patent office at which the application is first filed before protection is extended internationally and provides an indication of the attractiveness and accessibility of a country's patenting system.

OECD (2009) recommends using the inventor's country of residence when the objective is to measure inventive activity. However, the PATENTSCOPE database reports inventors' nationality rather than country of residence. Relying on nationality may distort measures of inventiveness, particularly in countries with high levels of immigration, where inventors may reside and work domestically while holding foreign citizenship.

Given the objectives of this research, the applicant's country of residence is the most appropriate assignment criterion. The analysis focuses on countries' ability to commercialise AI-related technologies and to capture the economic returns from AI-related knowledge, rather than solely on the geographic location of inventive activity. Patent ownership, as proxied by applicant residence, more accurately reflects control over intellectual property and the capacity of firms and countries to translate innovation into competitive advantage. Accordingly, all patents in the analysis are assigned to countries based on the applicant's country of residence.

In recent years, there has been increasing collaboration among researchers and firms across borders, resulting in patents with multiple applicants from different countries. To avoid double-counting while still recognising the contributions of all countries involved, fractional counting is employed. When a patent has applicants from multiple countries, each country receives a fractional share equal to one divided by the number of distinct countries of applicants. This approach ensures that the total count of each patent sums to one across all countries, maintaining consistency with aggregate statistics while appropriately distributing credit for collaborative innovations.

3.4.5. Mapping Patents to Industries

Patents are classified according to the IPC system, which organises inventions by technology field rather than by the economic sector in which they might be applied. However, the IIO tables are organised at the industry level. Hence, to combine the two sets of information, a concordance that maps technology classes to industries is needed.

Several concordances have been developed over the years to address this challenge. The Yale Technology Concordance (YTC), developed in the 1990s, linked IPC codes to Industry of Manufacture (IOM) and Sector of Use (SOU) codes. This was followed by the OECD Technology Concordance (OTC) Technology Concordance in 2002, which was built on top of the YTC by translating its IOM-SOU codes into International Standard Industrial Classification (ISIC) codes, making the data more internationally compatible (Johnson, 2002). The most recent and methodologically sophisticated approach is the Algorithmic Links with Probabilities (ALP) methodology developed by Lybbert and Zolas (2014). This approach uses text mining to create probabilistic crosswalks between patent and industry classifications. The methodology mines patent titles and abstracts for keywords extracted from industry descriptions, tabulates frequency matches by IPC subclass, and processes these frequencies into a probabilistic mapping from IPC codes to industries.

The key advantage of the ALP approach for this research is that it assigns each IPC code a set of industries with associated weights that sum to one, representing the estimated probability that a patent in that IPC class belongs semantically to each industry. This probabilistic assignment recognises that many technologies have applications across multiple industries and avoids forcing each patent into a single industry category. For example, a machine learning algorithm might be applied in finance, healthcare, manufacturing, and other sectors, and the ALP methodology distributes the contribution of the patent across these industries according to the probability weights derived from textual analysis.

The ALP concordance provides mappings from IPC codes to two-digit ISIC Revision 4 codes, which correspond exactly to the two-digit NACE Revision 2 codes used in the FIGARO IIO tables. This alignment makes the concordance directly applicable to our research without requiring further transformations. For each patent in the dataset, the IPC codes were first extracted, which are provided in the PATENTSCOPE data. These codes are then reduced to the IPC4 level (the four-character IPC classification) to match the level of detail in the ALP concordance. For each unique IPC4 code associated with a patent, the corresponding two-digit NACE Revision 2 industry codes are retrieved along with their probability weights from the ALP concordance. These fractional weights are then added to the industry totals of the respective country for the respective year. When combined with the fractional country counting for patents with multiple applicants, this approach ensures that each patent contributes appropriately to the country-industry-year cells where it is most relevant. The aggregation process yields weighted patent counts for each country-industry-year combination, where the counts may be non-integer values due to the fractional assignments, but this has no adverse consequences for the analysis.

3.4.6. Calculating Patent Stocks

The annual patent counts constructed through the above procedures represent flows, i.e., the number of new patent applications in each year. However, for the HOV framework, stock endowments need to be measured, which represent the accumulated knowledge capital available in each country-industry at a given point in time. Patent flows alone do not adequately capture this accumulated knowledge because innovations from previous years continue to contribute to productive capabilities even as they age. At the same time, the economic value and technological relevance of patents decline over time as technologies become obsolete, patents expire, or newer innovations supersede them.

To convert patent flows into stocks while accounting for depreciation, the standard Perpetual Inventory Method (PIM) approach is employed (Lach, 1995). The PIM approach is widely used in economics to construct capital stock measures from investment flows and applies the same fundamental logic to knowledge capital. The patent stock at time t is calculated using the recursive formula:

$$S_t = (1-\delta)S_{t-1} + F_t \tag{3.3}$$

where S_t represents the patent stock at time t, δ is the depreciation rate, F_t is the flow of new patent applications in year t. This equation states that the current stock equals the stock from the previous period, reduced by depreciation, plus the new patent flow from the current period.

Implementing the PIM requires specifying two key parameters: the initial stock level S_0 and the depreciation rate δ. Given that the PATENTSCOPE database contains patent records extending back to the 1950s, the patent stock in the year 2000 is initialised to the patent flow during that year, recognising that patents granted earlier than that will have largely depreciated by then. Starting in 2000 provides a decade of stock accumulation before the analysis period begins in 2010, helping ensure that the stock measures reflect a mature accumulation process rather than being driven primarily by the choice of initial conditions.

The depreciation rate δ is set to 0.15, which is a standard value in the literature and reflects empirical evidence on the rate of decay in returns from patent protection (Schankerman & Pakes, 1986). A 15% annual depreciation rate implies that a patent retains approximately 85% of its value after one year, 61% after three years, 20% after ten years, and less than 4% after 20 years. This depreciation profile is consistent with the limited duration of patent protection (typically 20 years from filing) and the reality that most of the economic value from patents is realised in the early years after grant. To ensure the robustness of the empirical findings, the analysis is run multiple times for different depreciation rates ranging from 0% to 30%.

Applying this methodology separately to AI-related patents and non-AI-related patents yields two patent stock series for each country-industry-year combination: p^i_{ai} and p^i_n. A descriptive analysis of these two patent stock series across countries over time is conducted to document patterns of knowledge accumulation and concentration to answer RQ 1. These stock measures, when divided by gross output, provide the factor requirement coefficients that enter the factor requirements matrix e' for use in calculating the measured factor content of trade. The specific queries from WIPO AI Index used to identify AI-related patents from the WIPO PATENTSCOPE database are documented in Appendix C.

3.5. Measuring Labour Endowments

The labour endowment vector measures the total labour services available in each country-industry and is measured in the number of people employed. For comparability with the FIGARO IIO tables, the goal is to construct a comprehensive employment dataset classified by NACE Revision 2 industries for all 45 countries.

The methodology developed by Labaj and Majzlíková (2023) is followed, which synthesises data from as few sources as possible to cover all of the 45 countries. The primary data source is EUROSTAT National Accounts employment data by industry, which provides employment figures for 64 two-digit NACE Revision 2 industries for EU member states and several other European countries (Eurostat, 2026b). This dataset is highly reliable and directly compatible with the FIGARO input-output tables.

For countries not fully covered by EUROSTAT, the OECD Trade in Employment data (OECD, 2025) supplements, which provide industry-level employment figures for 45 industries, and OECD Labour Force Survey employment data at the aggregate level (OECD, 2026a). The OECD data aggregates the employment data for a few industries. For a small number of developing non-OECD countries where industry-level employment data are not available from either EUROSTAT or OECD sources, aggregate employment data is used from the World Development Indicators database (World Bank, 2026). The aggregate employment through both the OECD and the World Bank database are disaggregated into the NACE Revision 2 industries using value-added shares from the FIGARO IIO tables. This imputation assumes that employment shares across industries follow a similar pattern to value-added shares, which is a reasonable approximation for countries at similar levels of economic development.

The resulting labour endowment vector λ has dimension $(N \cdot J) \times 1$ (where $N = 45$ countries and $J = 64$ industries) and contains employment levels for each country-industry combination. Dividing these employment levels by gross output from the FIGARO database yields labour requirement coefficients that enter the factor requirements matrix e'.

3.6. Measuring Capital Endowments

Capital stock data present greater challenges because there is no unified database that provides comprehensive and consistent capital stock measures across developed and developing countries at the industry level. Different statistical agencies use different concepts (gross capital stock versus net capital stock), different units of measurement (current prices versus constant prices with varying base years), and provide data at varying levels of industry aggregation.

The use of net capital stock data is prioritised, which accounts for the depreciation of physical assets over time and provides a more economically meaningful measure of productive capacity than gross capital stock or capital formation flows. Net capital stock represents the written-down value of fixed assets after accounting for wear and tear, obsolescence, and scrapping. This is conceptually analogous to the patent stock measures constructed using the PIM, where accumulated flows are depreciated over time.

Data on net capital stock are collected from multiple sources, each covering different geographic regions and providing varying levels of industry detail. For European countries, the primary source is EUROSTAT National Accounts capital stock data by industry, which provides net capital stock for 64 two-digit NACE Revision 2 industries for some European countries and at more aggregated industry levels for others (Eurostat, 2026a). For the United Kingdom, which exited the EU during the sample period, capital stock data are obtained from the UK Office for

National Statistics (Office for National Statistics, 2025), which provides the full 64-industry breakdown. For non-European OECD countries, including the United States, Japan, Korea, Canada, and Australia, net capital stock data come from the OECD STAN Database (OECD, 2026c), where these data are available at a more aggregated industry level than the full 64-industry classification. For China, capital stock estimates are taken from the Chinese KLEMS Database (Research Institute of Economy, Trade and Industry et al., 2023), which provides data through 2017 at various levels of industry aggregation. For India, the India KLEMS Database provides net capital stock data at different aggregation levels (Reserve Bank of India, 2026). For Switzerland, the Swiss National Statistics Office provides only the total net capital stock at the national level without an industry breakdown (Swiss Federal Statistical Office, 2026). For the remaining developing countries, total net capital stock data are obtained from the Penn World Tables Version 10, which provides estimates through 2019 (Feenstra et al., 2015).

The heterogeneity in data availability and format necessitates substantial imputation work to construct a complete and consistent capital stock dataset. The imputation strategy is designed to minimise the assumptions required while ensuring that the final data are usable for the factor content calculations. Countries are sorted in increasing order of data completeness, and imputation proceeds from countries with the most complete data to those with the least. When data are missing only for the final one or two years of the sample period, capital stock is extrapolated using GDP growth rates, under the assumption that capital stock grows at a similar rate to overall economic output in the short run.

When industry-level capital stock data are missing, but aggregate capital stock is available, imputation proceeds by identifying comparison countries with similar income per capita, value-added structures, and economy-wide capital intensity. Capital intensity (capital stock per unit of value added) is calculated for each industry in these comparison countries, and the average capital intensity across comparison countries is used to estimate the industry-level capital stocks of the missing country from its observed value-added data. The estimated industry-level stocks are then rescaled proportionally to match the observed aggregate capital stock for that country, ensuring consistency with the known total.

All capital stock data are converted to a common unit of measurement to enable meaningful comparisons and aggregations. Since the majority of countries provide capital stock data in millions of euros, this is chosen as the base unit. Capital stock figures reported in other currencies are converted using annual average exchange rates from the European Central Bank (ECB) (European Central Bank, 2026). Capital stock data reported in constant prices with base years different from the analysis years are adjusted using GDP deflators to bring them to current prices for the relevant year.

The resulting capital endowment vector κ has dimension $(N \cdot J) \times 1$ (where $N = 45$ countries and $J = 64$ industries) and contains capital stock levels for each country-industry combination. Dividing these values by gross output yields capital stock requirement coefficients for the factor requirements matrix e'. It must be acknowledged that the capital stock data involves more imputation and uncertainty than the labour or patent data. However, since capital serves as a control variable rather than being the primary focus of the research, this limitation is acceptable.

3.7. Constructing the Measured Factor Content of Trade

With the factor endowment data constructed as described above, the components required to compute the measured factor content of trade can now be assembled using equation 3.2, following the methodology of Trefler and Zhu (2010). The first step is the construction of the factor requirements matrix e', which records the amount of each factor used per unit of gross output in each country–industry pair. This matrix is obtained by element-wise division of each factor endowment vector by the corresponding gross output vector X from the FIGARO database. Gross output in FIGARO measures the total value of production in each country–industry, including both intermediate and final goods, expressed in millions of euros.

This procedure is applied separately to the four factors considered in the analysis: AI-related patent stock, non-AI-related patent stock, labour, and capital stock. The resulting vectors of factor requirement coefficients are then transposed and stacked to form the matrix e', which has dimension $F \times (N \cdot J)$, where $F = 4$ denotes the number of factors, $N = 45$ the number of countries, and $J = 64$ the number of industries. Denoting countries by c and industries by i, the matrix takes the form

$$e' = \begin{pmatrix} p^{ai}_{c,i} & \cdots & p^{ai}_{c,J} & \cdots & p^{ai}_{N,i} & \cdots & p^{ai}_{N,J} \\ p^{n}_{c,i} & \cdots & p^{n}_{c,J} & \cdots & p^{n}_{N,i} & \cdots & p^{n}_{N,J} \\ l_{c,i} & \cdots & l_{c,J} & \cdots & l_{N,i} & \cdots & l_{N,J} \\ k_{c,i} & \cdots & k_{c,J} & \cdots & k_{N,i} & \cdots & k_{N,J} \end{pmatrix}$$

where p^{ai} and p^{n} denote direct factor requirements of AI-related and non-AI-related patent stocks, respectively, while l and k denote direct labour and capital stock requirements.

The second key component is the global Leontief inverse L, which is derived from the FIGARO IIO tables. These tables provide the matrix Z, whose elements z^{cn}_{ij} represent the value of intermediate inputs from industry i in country c used by industry j in country n. From Z, the technical coefficients matrix A is constructed by dividing each column by the corresponding gross output, yielding $A = Z\hat{X}^{-1}$, where $\hat{X}$ is a diagonal matrix with gross output on the diagonal. Each element a^{cn}_{ij} thus measures the value of inputs from country c's industry i required to produce one euro of output in country n's industry j.

The Leontief inverse is then given by $L = (I - A)^{-1}$, where I is the identity matrix of dimension $(N \cdot J) \times (N \cdot J)$. An element l^{cn}_{ij} captures the total—direct and indirect—output of country c's industry i required to produce one euro of final output in industry j of country n. Diagonal blocks of L represent domestic inter-industry linkages, while off-diagonal blocks capture international production linkages through trade in intermediate inputs.

Total factor requirements are obtained by premultiplying the Leontief inverse by the direct factor requirements matrix, yielding $A_f = e' \cdot L$. The resulting matrix has the same dimension as e' but now reflects the total amount of each factor required per unit of output in each country–industry, accounting for all intermediate input linkages. This step constitutes a central advantage of the Trefler and Zhu (2010) approach, as it ensures that factor inputs embodied in traded intermediates are fully incorporated.

The final component is the country-specific net trade vector T^c, which records exports and imports by industry for country c and is constructed using the same FIGARO IIO tables. The vector has dimension $(N \cdot J) \times 1$ and includes country c's total exports by industry, x_j^{c*}, as well as bilateral imports from each trading partner n, m_j^{nc}, which enter with a negative sign:

$$T^c = \begin{pmatrix} x_i^{c*} \\ x_j^{c*} \\ \vdots \\ x_J^{c*} \\ \vdots \\ -m_i^{nc} \\ -m_j^{nc} \\ \vdots \\ -m_J^{nc} \\ \vdots \\ -m_i^{Nc} \\ -m_j^{Nc} \\ \vdots \\ -m_J^{Nc} \end{pmatrix}.$$

where x_j^{c*} denotes the total exports in industry j of country c to all trading partners, and m_j^{nc} denotes the imports in industry j of country c from country n. The measured factor content of trade of country c is then calculated as:

$$f^c = \begin{pmatrix} f_c^{P^{ai}} \\ f_c^{P^n} \\ f_c^L \\ f_c^K \end{pmatrix} \equiv A_f \cdot T^c = e' \cdot L \cdot T^c$$

where each element represents the net content of AI-related patents, non-AI-related patents, labour, and capital embodied in country c's net exports. Positive values indicate net exports of the corresponding factor, while negative values indicate net imports. This calculation is performed for each country and year over the period 2010–2021, yielding a panel of measured factor content values that forms the basis for the subsequent empirical analysis.

3.8. Constructing the Predicted Factor Content of Trade

The predicted factor content of trade is derived from the classical HOV framework and corresponds to the expression in equation 3.1. It depends on two key components: countries' factor endowments and their shares in global consumption. The construction, therefore, proceeds in two steps.

The starting point is the country-specific factor endowment vector V^c, which is obtained by aggregating factor levels across all industries within each country. For each factor, endowments are computed by summing industry-level values. For example, country c's total endowment of AI-related patent stock is given by $V_c^{P^{ai}} = \sum_{j=1}^{J} P_{ai,cj}$, with analogous expressions for non-AI-related patent stock, labour, and capital. This yields a factor endowment vector of dimension $F \times 1$ for each country:

$$V^c = \begin{pmatrix} P^{ai} \\ P^n \\ L \\ K \end{pmatrix}$$

The corresponding world factor endowment vector, V^W, is constructed by summing country-level endowments across all N countries, including the rest of the world:

$$V^W = \sum_{c=1}^{N} V^c$$

The second component required to compute predicted factor content is country c's share in global consumption, denoted σ^c. Following standard practice in the HOV literature (Trefler, 1995), this share is measured as the ratio of domestic absorption to world absorption, where absorption is defined as GDP net of the trade balance. Formally,

$$\sigma^c = \frac{GDP^c - TB^c}{GDP^W - TB^W}$$

where GDP^c and TB^c denote country c's gross domestic product and trade balance, respectively, and GDP^W and TB^W are their global counterparts. All variables are calculated using data from the FIGARO IIO tables.

Given V^c, V^W, and σ^c, the predicted factor content of trade for country c is obtained directly from the Vanek equation 3.1. This yields a vector of dimension $F \times 1$ containing the predicted net exports of each factor, AI-related patent stock, non-AI-related patent stock, labour, and capital. As with the measured factor content, this calculation is performed for each country and each year over the sample period 2010–2021, resulting in a panel of predicted factor content values used in the subsequent empirical analysis.

3.9. Statistical Testing of the HOV Model

The empirical validity of the HOV framework is evaluated by comparing the measured factor content of trade, f^c, with the predicted factor content, $\tilde{F}^c$, using three complementary statistical tests: sign tests, rank tests, and regression analysis. The first two tests follow the methodology established by Leamer (1980) and have been widely applied in subsequent HOV studies (Trefler, 1995; Trefler & Zhu, 2010).

Before conducting these tests, the data undergo two preprocessing steps to ensure meaningful comparisons. First, deviations between measured and predicted factor content are computed for each country–factor pair:

$$\varepsilon_f^c = f_f^c - \tilde{F}_f^c \tag{3.4}$$

These deviations quantify the extent to which observed trade patterns diverge from HOV predictions, providing insight into systematic biases and potential sources of prediction error.

Next, two normalisation procedures are applied to the deviations to make them comparable across factors and countries. The first normalisation addresses the problem identified by Trefler (1995) that different factors are measured in different units (patents vs thousands of workers vs millions of euros of capital), making direct comparisons difficult. To address this, the data of each factor is divided by the standard deviation of that factor:

$$\sigma_f = \sqrt{\frac{\sum_c \left(\varepsilon_f^c - \bar{\varepsilon}_f\right)^2}{N-1}} \tag{3.5}$$

where $\bar{\varepsilon}_f$ is the average deviation across all countries for factor f. This transformation standardises each factor to have a common scale.

The second normalisation addresses country size differences. Larger economies naturally have larger factor contents of trade in absolute terms, which could make the statistical tests sensitive to a few large countries. To control for this, each observation is weighted by the square root of the consumption share of the country $(\sigma^c)^{1/2}$ as recommended by Trefler (1995). This weighting ensures that deviations are measured relative to country size, preventing large countries from dominating the test statistics.

After these normalisations, the three tests are conducted. The sign test evaluates whether the measured and predicted factor contents exhibit the same direction for each country–factor observation. According to the HOV model, a country that is relatively abundant in a factor ($\tilde{F}_f^c > 0$) should be a net exporter of that factor in measured terms ($f_f^c > 0$), and vice versa for relatively scarce factors. The test calculates the proportion of country–factor pairs for which the measured and predicted values share the same sign, expressing this as a percentage of total observations. A perfect correspondence would yield 100% sign matches, whereas random alignment would result in approximately 50%. High percentages indicate that the HOV framework correctly identifies the direction of factor trade flows, even if the magnitude of the measured factor content differs from predictions.

The rank test examines whether pairwise comparisons of factor contents across different factors have the same ordering in measured and predicted data. For example, consider country c with two factors f and f'. The rank test checks whether $f_f^c > f_{f'}^c$ implies $\tilde{F}_f^c > \tilde{F}_{f'}^c$. This is evaluated for all possible pairs of factors within each country. The test counts the number of pairwise comparisons where the ordering is the same in measured and predicted data and expresses this as a percentage of total comparisons. The rank test assesses whether the HOV framework can correctly predict the relative importance of different factors in shaping the trade patterns of each country, which is a stronger requirement than simply getting the signs correct.

The third test regresses the measured factor content on the predicted factor content using Ordinary Least Squares (OLS):

$$f_f^c = \alpha + \beta \tilde{F}_f^c + u_f^c \tag{3.6}$$

The slope coefficient β and the coefficient of determination R^2 are employed as indicators of goodness of fit. A perfect match between measured and predicted values would yield $\beta = 1$ and $R^2 = 1$. In practice, β is expected to be positive but potentially different from one, and R^2 to be less than one, reflecting the fact that real-world trade patterns are influenced by factors beyond simple endowment differences (such as trade costs, non-homothetic preferences, and imperfect competition). This regression test looks at the "missing trade" puzzle mentioned by Trefler (1995). It helps to examine whether the HOV predictions are biased in a systematic direction (which would be indicated by an intercept significantly different from zero or a slope significantly different from one).

These three tests are conducted separately for each year in the sample and for each factor, enabling an assessment of whether the HOV framework performs better for certain factors than for others and whether its performance has evolved. Particular attention is paid to comparing the performance of AI-related patents and non-AI-related patents versus traditional factors (labour and capital). If patents perform similarly well to traditional factors in the sign and rank tests, this provides evidence that knowledge endowments shape trade patterns through the same comparative advantage mechanism that operates for conventional factors. If patents perform poorly relative to other factors, this would suggest that either the knowledge is not yet sufficiently specialised to drive trade patterns, or that other mechanisms (such as technology transfer, licensing, or non-tradable aspects of AI) are more important than embodied factor content. These results directly address RQ 2 regarding the extent to which AI patent stock endowments predict trade patterns according to the HOV framework.

Two methodological limitations must be acknowledged regarding the HOV framework and its empirical implementation. First, the relationship between patent stocks and trade patterns could be endogenous. Countries that trade more intensively in technology-intensive goods may also be more likely to file patents, either because trade stimulates innovation or because both trade and patenting are driven by common underlying factors such as institutional quality, human capital endowments, or R&D investment. This endogeneity makes it difficult to establish a clear causal direction from patent stocks to trade flows. This thesis tests whether the observed correlation between patent endowments and factor content of trade is consistent with the predictions of the HOV framework, without claiming to have identified a causal effect. The results should be interpreted as evidence of association rather than causation.

Second, the HOV framework relies on the assumption of consumption similarity, as formalised by Trefler and Zhu (2010). This assumption states that countries consume a proportion of world output consistent with their share of world GDP. Deviations from this assumption, which can arise from non-homothetic preferences, home bias, or geographic sourcing patterns, can lead to systematic errors in the factor content predictions. While the literature has shown that allowing for these features improves HOV predictions (Stehrer, 2014), the baseline specification in this thesis maintains the consumption similarity assumption for comparability with the core HOV literature. To verify this, a robustness check is conducted following Trefler and Zhu (2010) to identify industries with the largest violations of consumption similarity and checking if excluding them improves the fit with the HOV predictions.

3.10. Measuring Comparative Advantage in AI-related Patents

Beyond assessing the validity of the HOV framework, the analysis aims to identify which countries possess a comparative advantage in AI-related patents. Following Leamer (1980), comparative advantage is revealed through relative factor abundance, which can be inferred from the measured factor content of trade. A country is considered relatively abundant in factor f relative to factor f' if the ratio of these factors in production exceeds the corresponding ratio in consumption.

For country c, production of each factor is assumed to equal its endowment V_f^c under full employment. Consumption of each factor is then calculated by subtracting the measured net factor content of trade from the endowment:

$$C_f^c = V_f^c - f_f^c$$

Country c is then considered relatively abundant in AI-related patents compared to non-AI-related patents if:

$$\frac{V_c^{Pai}}{V_c^{Pn}} > \frac{C_c^{Pai}}{C_c^{Pn}}$$

This condition can be rearranged algebraically to show that it is equivalent to:

$$\frac{f_c^{Pai}}{V_c^{Pai}} > \frac{f_c^{Pn}}{V_c^{Pn}}$$

In other words, a country is relatively abundant in AI-related patents if the share of its AI-related patent endowment that is exported (as embodied factor content) exceeds the share of its non-AI-related patent endowment that is exported. Countries where this condition holds have revealed a comparative advantage in AI-related knowledge. To quantify the strength of comparative advantage and enable ranking of countries, the relative factor abundance ratio for AI-related patents is calculated as the production ratio over the consumption ratio:

$$RFA_c^{AI} = \frac{V_c^{Pai}/V_c^{Pn}}{(V_c^{Pn} - f_c^{Pai})/(V_c^{Pn} - f_c^{Pn})} \tag{3.7}$$

A value of the relative factor abundance ratio greater than one indicates that a country holds a comparative advantage in AI-related patents relative to non-AI-related patents, whereas a value below one signals the absence of such an advantage. The magnitude of the ratio reflects the strength of the comparative advantage.

As an additional robustness check, the bilateral relative factor abundance is also calculated following Debaere (2003). This approach compares country c directly with each other country n, asking whether country c is relatively abundant in AI-related patents compared to country n. Specifically, country c is relatively abundant in AI-related patents compared to country n if:

$$\frac{V_c^{Pai}/V_c^{Pn}}{V_n^{Pai}/V_n^{Pn}} > 1$$

For each country, the number of bilateral comparisons in which it is relatively abundant in AI-related patents is counted. Countries with high counts are relatively abundant in AI patents compared to most other countries, while those with low counts are relatively scarce. This bilateral approach provides an alternative ranking that does not rely on factor content calculations and serves as a cross-check on the results from the approach by Leamer (1980).

Both ranking methods are applied to the most recent year of data (2021) to identify current comparative advantage positions, addressing RQ 3. The rankings are also calculated for all years in the sample to enable analysis of changes over time for RQ 4. Of particular interest is whether the position of the EU has improved, stagnated, or deteriorated relative to the US, China, and other major trading partners.

3.11. Robustness Checks and Sensitivity Analysis

To assess the stability of the findings, several robustness checks and sensitivity analyses are conducted. First, a robustness check is conducted on consumption similarity violations. As mentioned earlier, the HOV framework relies on the consumption similarity assumption, which states that countries consume a proportion of world output consistent with their share of world GDP. As noted by Trefler and Zhu (2010), deviations from this assumption can lead to systematic errors in factor content predictions. To identify industries where consumption similarity is most severely violated, the variance of prediction errors is calculated at the industry level following the methodology of Trefler and Zhu (2010). Specifically, for each factor f, industry g, and country-pair (i, j), the error component is defined as:

$$\varepsilon_{fgij} = A_{fgj}\left(C_{gij} - s_i C_{gwj}\right)$$

where A_{fgj} is the total factor requirement coefficient for factor f in industry g of country j, C_{gij} is the consumption of good g in country i produced in country j, s_i is the share of world consumption of country i, and C_{gwj} is world consumption of good g produced in country j. The variance of these errors is then computed for each industry:

$$\sigma_g^2 = \frac{1}{N^2} \sum_i \sum_j \left(\varepsilon_{fgij} - \bar{\varepsilon}_{fg}\right)^2$$

Industries with the highest variances are those where departures from consumption similarity are most pronounced. These industries are then excluded from the analysis to check whether the HOV fit improves, serving as a robustness check of the performance of the HOV model when the consumption similarity assumption is better satisfied.

Second, to assess the sensitivity of the comparative advantage results to any particular industry, the relative factor abundance ratio is re-estimated by excluding one industry at a time. This procedure is conducted for all 64 industries in the FIGARO database. If removing a single industry significantly changes the comparative advantage rankings, this would suggest that the results are driven by that specific sector rather than reflecting a broader pattern across the economy. Conversely, if the rankings remain stable across all exclusions, this provides confidence that the findings are not driven by any particular industry.

Third and finally, a robustness check is done on the comparative advantage results by considering all PCT applications and by looking at different patent depreciation rates.

As discussed in Section 3.4.1, the indicator used for creating patent stocks is PCT applications that have entered the national phase, as these represent patents for which applicants have made a financial commitment to pursue protection in multiple jurisdictions. However, an alternative measure is to use all PCT applications, regardless of whether they enter the national phase. This broader measure may capture a wider range of innovative activity. To test the robustness, the entire analysis is repeated using total PCT applications. If the comparative advantage rankings remain similar, it increases confidence in our results.

The construction of patent stocks using the PIM also required an assumption about the depreciation rate. As discussed in Section 3.4.6, the baseline analysis uses $\delta = 0.15$, which is standard in the literature on knowledge stocks (Schankerman & Pakes, 1986). However, there is uncertainty about the true rate of knowledge obsolescence in rapidly evolving technological fields, particularly for AI, where the pace of innovation is exceptionally fast. To assess the sensitivity of the results to this assumption, patent stocks are recalculated using different depreciation rates ranging from $\delta = 0$ (no depreciation) to $\delta = 0.30$ (rapid obsolescence). For each depreciation rate, the factor content predictions and the relative factor abundance indices are recalculated. If the comparative advantage rankings remain stable across this range, it provides confidence that the patent depreciation rate is not driving the results.

Taken together, the above checks provide comprehensive evidence on the robustness of the empirical results and help identify potential sources of sensitivity in the HOV framework when applied to AI-related knowledge endowments.

4

Descriptive Results of Factors

This chapter presents descriptive evidence on the distribution and evolution of factor endowments across countries from 2010 to 2021, addressing RQ 1. This analysis establishes the foundation for the subsequent empirical tests of the HOV framework by documenting how AI-related knowledge, alongside general innovative capacity and traditional factors, is distributed globally and how this distribution has changed over time.

The analysis focuses primarily on patent stocks. As described earlier in Chapter 3.4, patent stock data are constructed from PCT applications that entered the national phase in at least one national patent office. These applications are converted to stocks using the PIM approach with a 15% annual depreciation rate. The stocks are measured for 45 countries plus a rest-of-world aggregate, spanning the period 2010 to 2021, and are separated into patents related to AI and not related to AI using the WIPO AI Index (Appendix C). Section 4.1 and 4.2 show the distribution of AI-related and non-AI-related patent stocks, respectively. Section 4.3 assesses the trends in AI intensity to verify the emergence of AI as a GPT in recent years. Section 4.4 looks at the distribution of AI patents across industries. Section 4.5 briefly examines labour and capital endowments. Section 4.6 finally looks at all four factors holistically for the US, EU, and China and sets the context for HOV analysis. Overall, the descriptive analysis answers whether AI knowledge accumulation is becoming concentrated in particular countries, if the EU is losing ground relative to major competitors, and if AI represents a distinct domain of specialisation separate from general innovative capacity.

4.1. Distribution of AI-Related Patent Stocks

The global distribution of AI-related patent stocks as of 2021 reveals a concentration of AI knowledge in a small number of countries. Figure 4.1 shows both the trend in shares of AI-related patents from 2010 to 2021 for the five leading AI-patenting countries.

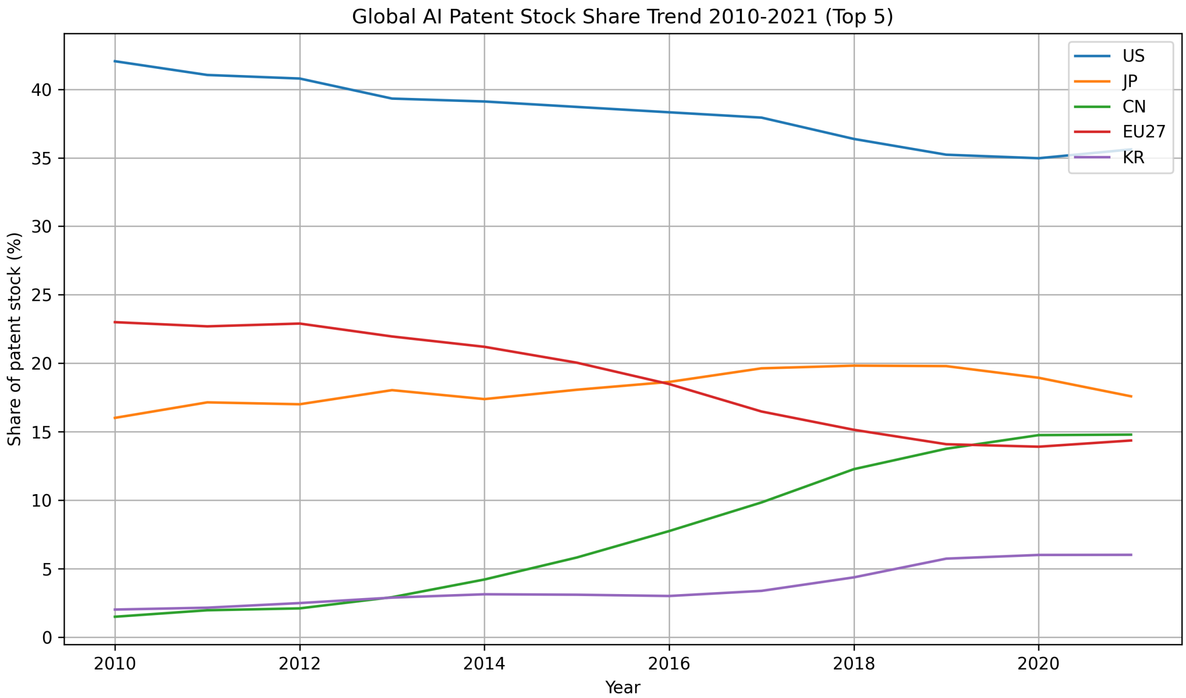


Figure 4.1: Trend of Global Share of AI-related Patents

While the US remains the global leader, its share declined by roughly 5 percentage points between 2010 and 2021. This reflects slower growth relative to China rather than an absolute decline in US AI-related patenting. The EU's trajectory is more concerning. Its global share fell by approximately 9 percentage points, indicating that European AI-related patents have not kept pace with major competitors. China exhibits the most substantial change. Its share of global AI patent stocks rose rapidly after 2012 by 13 percentage points, overtaking the EU by 2021. Japan's share remained broadly stable, while Korea experienced modest gains.

Within the EU, AI capabilities are unevenly distributed. Germany and France dominate in absolute terms, reflecting the large economies of these countries and established industrial and research bases. This is seen in Figure 4.2. The Netherlands and Sweden are two countries within the EU that have increased their shares of EU AI-related patents very slightly during this same period.

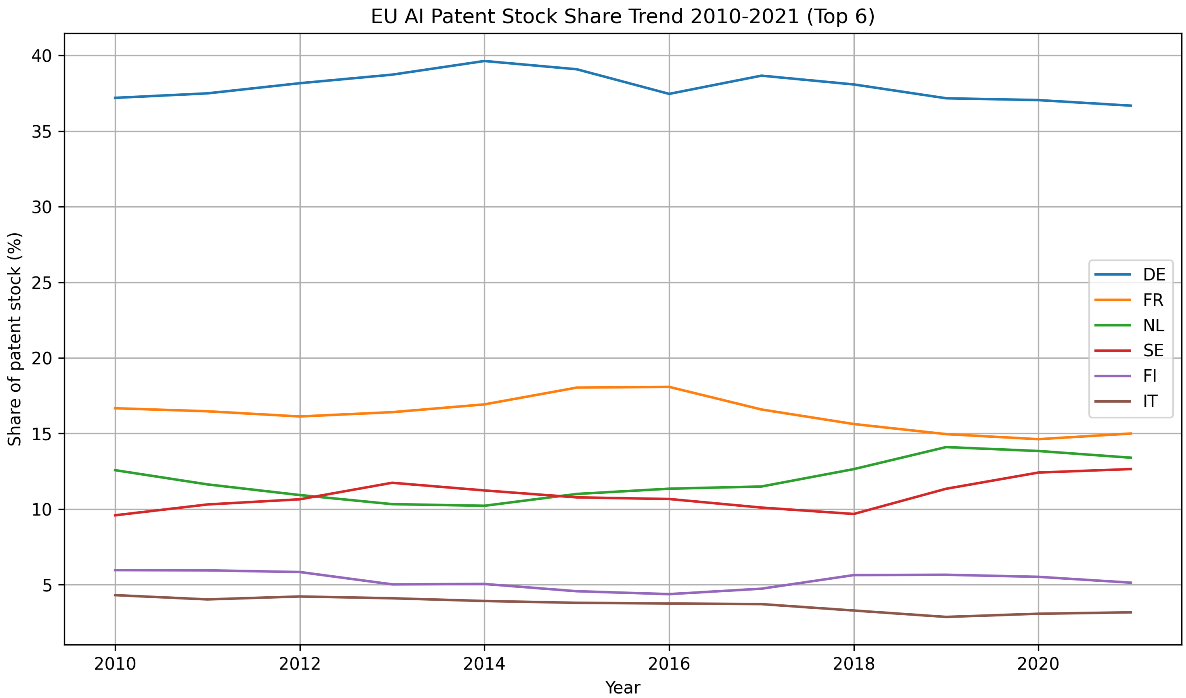


Figure 4.2: Trend of EU Share of AI-related Patents

Overall, the five leading countries, i.e., the US, EU, China, Japan, and Korea, account for nearly 90% of global AI patent stocks, highlighting the extreme concentration of AI knowledge. For the EU, the concern is not whether it is among the leaders, which it clearly is, but whether its position within the leading group is sustainable given the declining trend in its share.

4.2. Distribution of non-AI-Related Patent Stocks

To assess whether the patterns observed for AI-related patents reflect broader innovative capacity or represent AI-specific specialisation, it is necessary to examine trends in non-AI-related patent stocks. Figure 4.3 presents similar trends for non-AI patent stocks. The global concentration pattern is similar, but the dynamics differ. The share of non-AI patents in the EU declined by about 6 percentage points from 2010 to 2021, which is substantial, but notably smaller than the decline observed for AI patents.

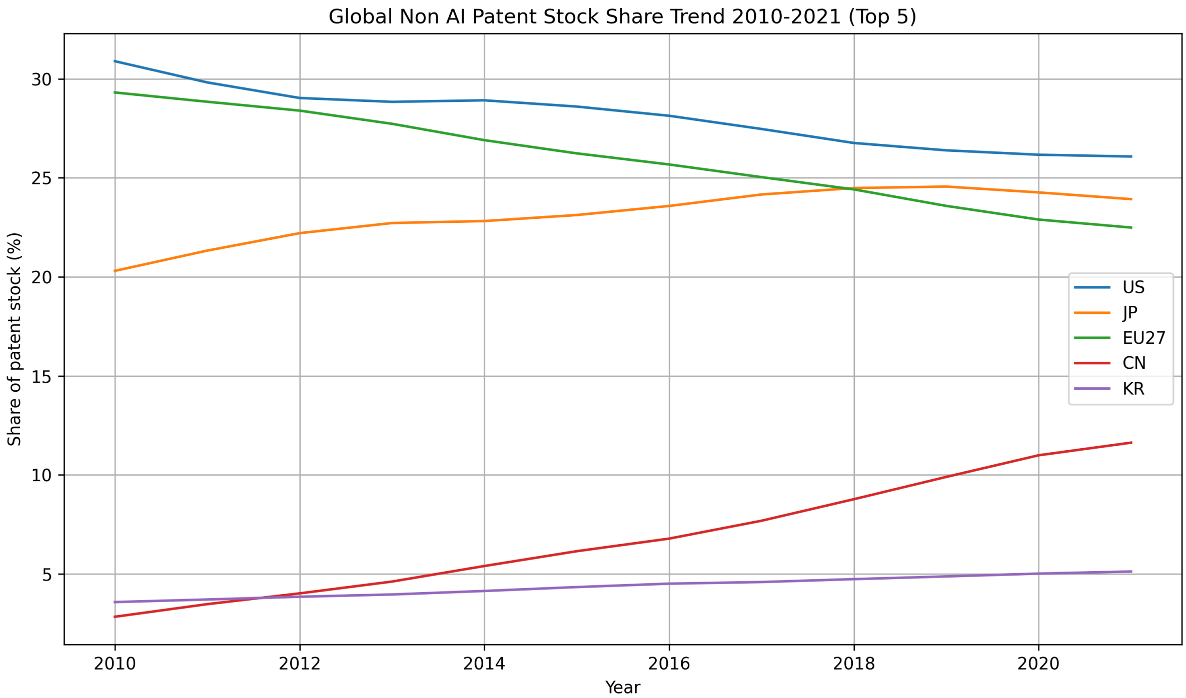


Figure 4.3: Trend of Global Share of non AI-related Patents

This comparison indicates that the EU's loss of ground is more pronounced in AI than in innovation overall. By contrast, the US experienced similar declines in both AI and non-AI patents, while China gained share in both types of patents. These patterns suggest that the challenge of the EU is not simply maintaining its share of global innovation, which has always been difficult given the rapid economic development and scale of China. The more fundamental problem is that the EU is losing ground faster in AI than in other technological domains, suggesting that European innovative activity is not sufficiently concentrated in what may be the most economically consequential technology of the coming decades.

4.3. AI Intensity Trends

To assess specialisation in AI, Figure 4.4 reports AI intensity, defined as the share of AI patent stocks in total patent stocks. If AI is indeed emerging as a distinct GPT driving a new wave of innovation, a rising AI intensity over time is expected as innovative effort shifts toward this domain.

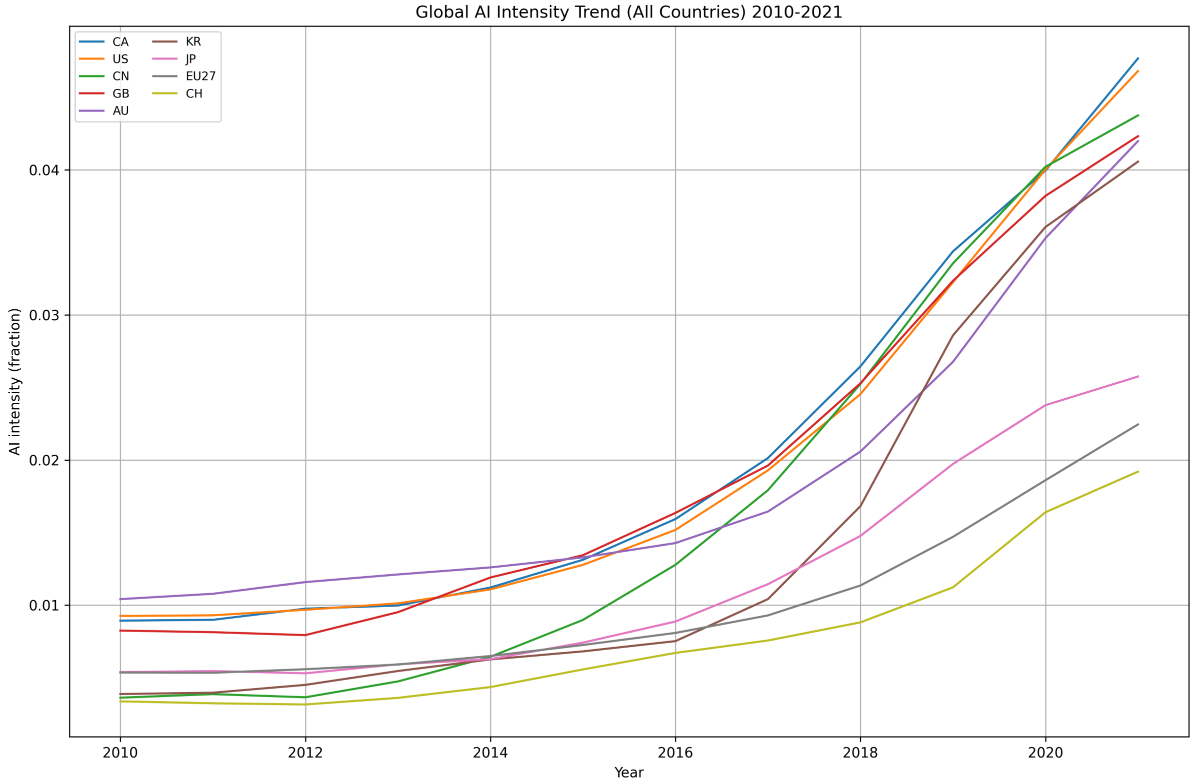


Figure 4.4: Global AI Intensity Trend

The data confirm a clear upward trend in AI intensity across almost all countries from approximately 2014 onward. The rising intensity suggests that innovators across countries have been redirecting effort toward AI-related technologies. However, the level of AI intensity varies substantially across countries. As of 2021, countries including Canada, the US, China, the United Kingdom, Australia, and Korea have reached AI intensities close to 5%, meaning that approximately 1 in 20 patents filed relates to AI. In contrast, the EU as a whole lags at nearly 2.5% AI intensity, only half the level of the leading countries. This gap suggests that European innovative activity remains more concentrated in traditional technology domains and has been slower to shift toward AI-related applications.

Figure 4.5 shows that the heterogeneity is more pronounced within Europe. Ireland, the Netherlands, Sweden, and Finland exhibit higher AI intensity than larger economies of Germany, France, and Italy.

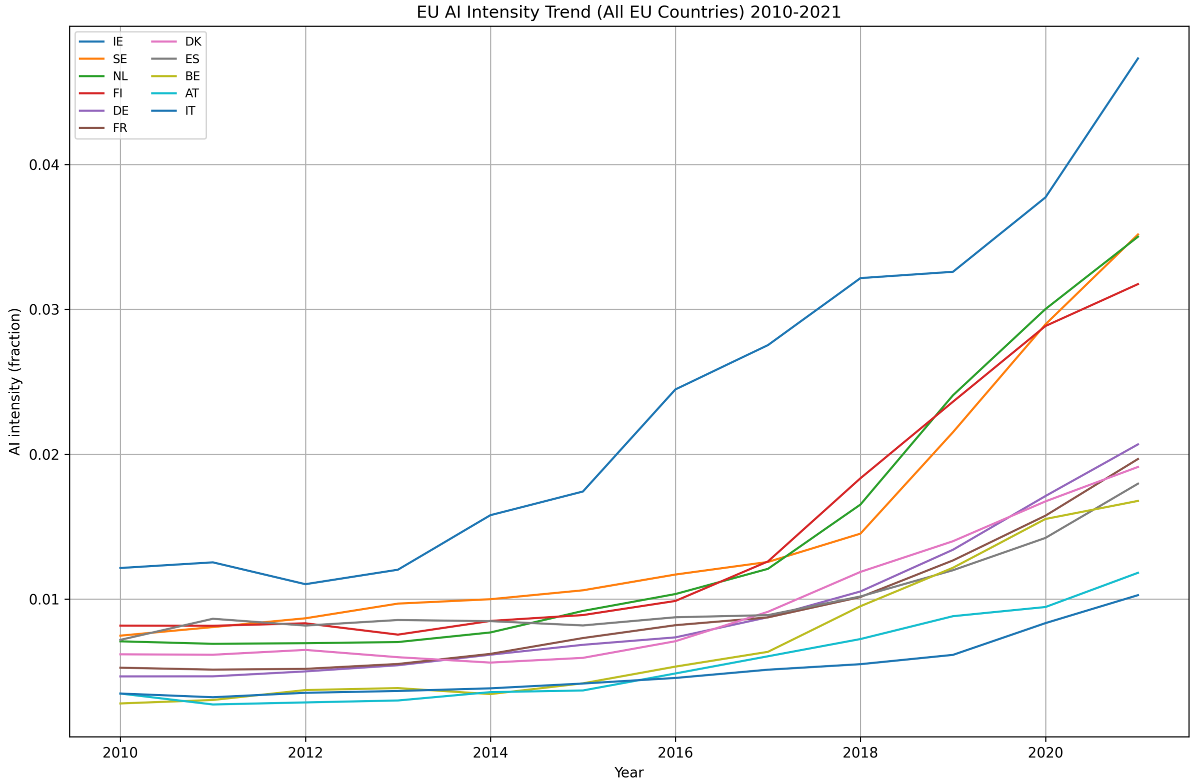


Figure 4.5: EU AI Intensity Trend

The rising AI intensity observed across countries provides empirical support for treating AI as a distinct technological domain and for the conceptual framework outlined in Chapter 1 that positions AI as a potential new GPT.

4.4. Industry-Level Patterns of AI Specialisation

Beyond country-level aggregates, it is informative to examine which industries exhibit the highest number of AI-related patents and what the distribution looks like within those industries. Figure 4.6 shows the trend of the distribution of global AI-related patents across industries. The description of the industry codes used can be viewed in Appendix E. The distribution shows that nearly 50% of the AI-related patents come from the manufacture of computers, software and optics (Industry Code: C26), followed by 13% from motion picture, video, television programme production, programming and broadcasting activities (Industry Code: J59_60). Also, the distribution of AI-related patents across sectors has not changed much from 2010 to 2021.

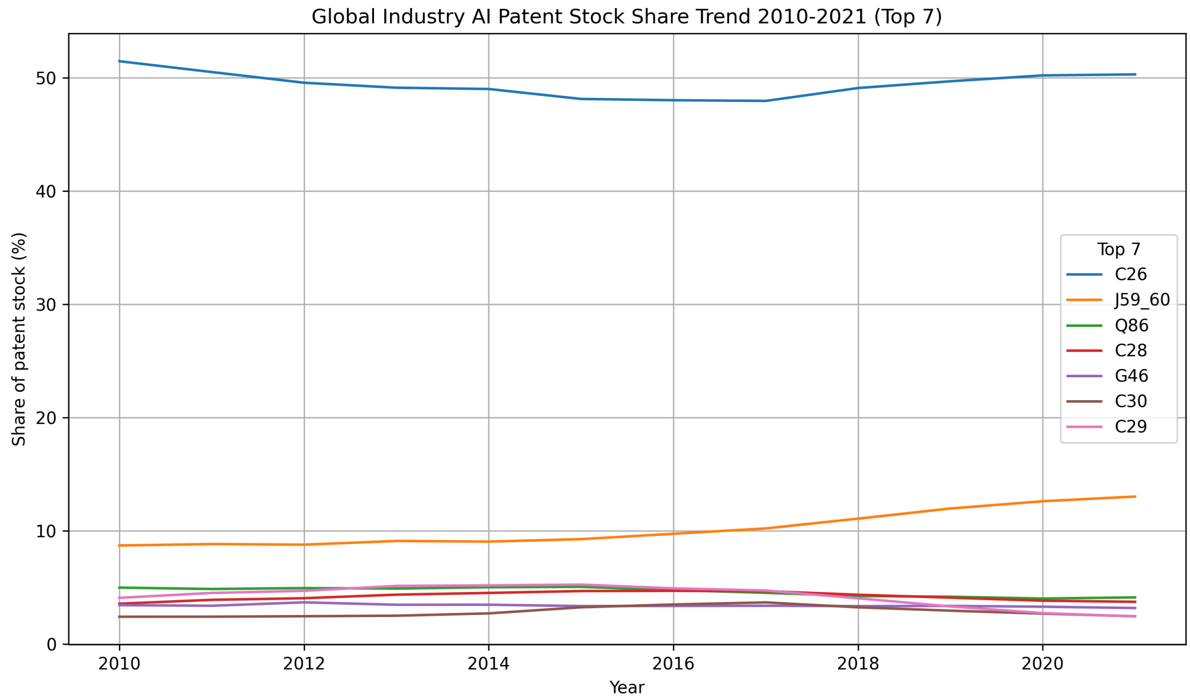
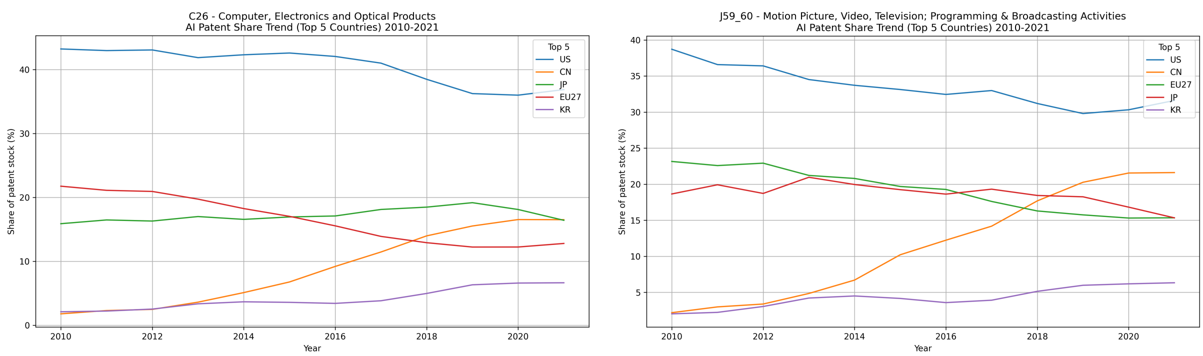


Figure 4.6: Industry Trend of Share of AI-related Patents

Figure 4.7 shows that the country-level patterns observed for global AI-related patents are more pronounced within these two dominant industries. In the manufacture of computers, electronics, and optical products (C26), the share of China rose from approximately 1% in 2010 to 17% by 2021, overtaking the EU whose share declined from 22% to 13% over the same period. The US maintained the leading position but experienced a relatively more modest decline from 43% to 37%. A similar trajectory emerged in motion picture, video, and broadcasting activities (J59_60), where the share of China increased from around 2% to 22%, while share of the EU fell from 23% to 16%. These industry-specific trends indicate that the loss of ground in AI patents for the EU is particularly acute in the sectors containing nearly two-thirds of global AI patents.



(a) Trend of Global Share of AI-related Patents in C26: Manufacture of Computer, Electronics, and Optical Products

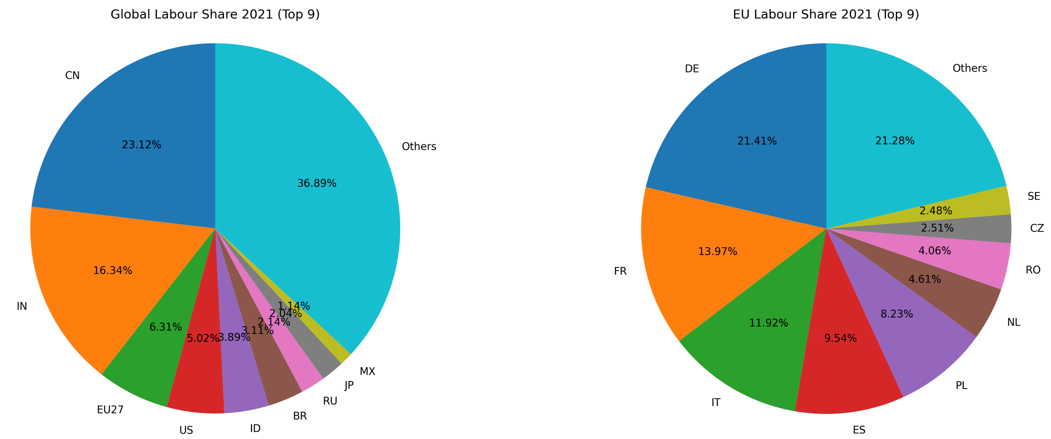
(b) Trend of Global Share of AI-related Patents in J59_60: Motion Picture, Video, Television; Programming & Broadcasting Activities

Figure 4.7: Trend of Global Share of AI-related Patents in C26 and J59_60

4.5. Traditional Factor Endowments: Labour and Capital

While the focus of this research is on knowledge endowments measured through patents, labour and capital endowments are included in the analysis as control factors as mentioned in Chapter 1.2. Key patterns of these two endowments are provided here to provide a well-rounded context of the distribution of factor endowments of the main countries

Figure 4.8 contains the distribution of labour endowments as of 2021. The global distribution matches our prior expectations, with China and India together accounting for the majority of world employment due to their large populations. The EU and the US follow as significant but smaller shares of the global labour supply. Within the EU, Germany, France, Italy, and Spain account for the largest employment shares, reflecting both population size and economic structure. Labour endowments have remained relatively stable over the 2010-2021 period, with shares changing only modestly.



(a) Global Share of Labour as of 2021

(b) EU Share of Labour as of 2021

Figure 4.8: Share of Labour as of 2021

Capital stock distributions show more dynamic patterns, as seen in Figure 4.9. As of 2021, China has matched the EU in share of global net capital stock, reflecting high investment rates and capital accumulation in the last decade that have supported the rapid economic growth of China. The US maintains the largest capital stock globally, while the share of EU global capital has fallen notably since 2010, indicating that European investment, while substantial in absolute terms, has not kept pace with capital accumulation in other major economies, particularly China.

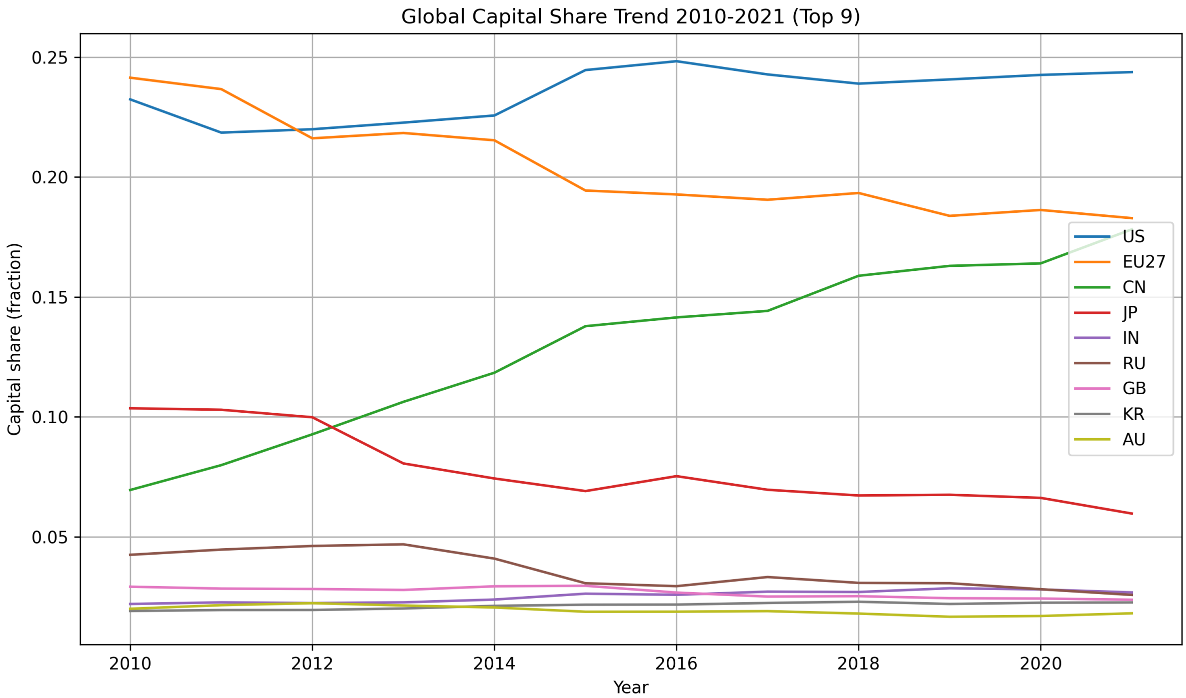


Figure 4.9: Trend of Global Share of Net Capital Stock

4.6. Approaching the HOV Framework: Predicted Factor Content of Trade in the Triad

Before turning to the empirical results of the HOV analysis, examining the relative positions of factor endowments and consumption shares provides intuitive insight into what the classical HOV model predicts. As explained in Chapter 3.8, the predicted factor content of trade is calculated using the Vanek equation, which compares a country's factor endowments with its share of world consumption. Figures 4.10 and 4.11 display the factor endowment and consumption shares for the EU, China, and the US in 2010 and 2021, offering a visual representation into the HOV framework.

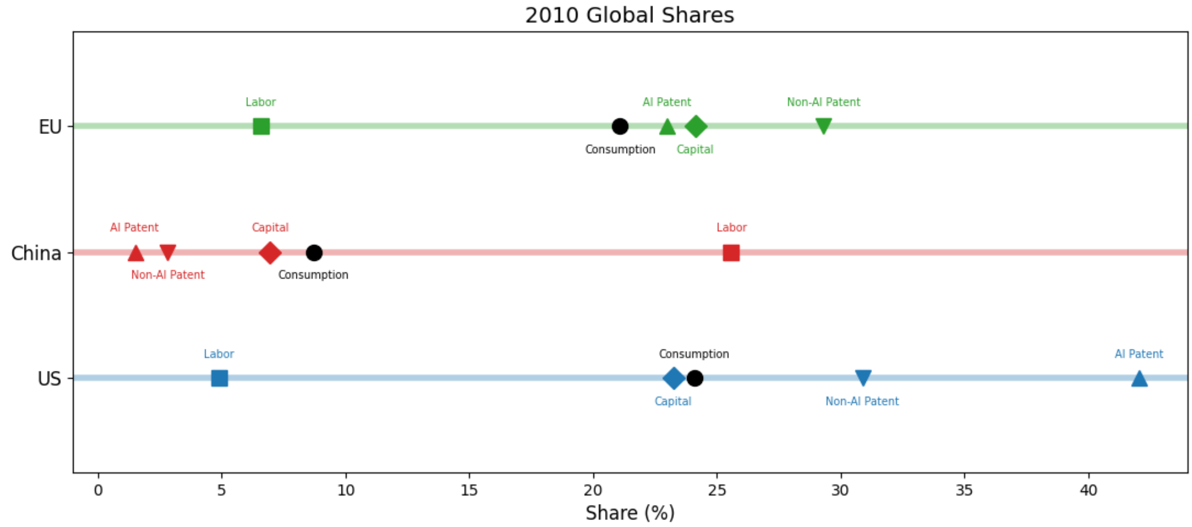


Figure 4.10: Factor and Consumption Shares of Triad in 2010

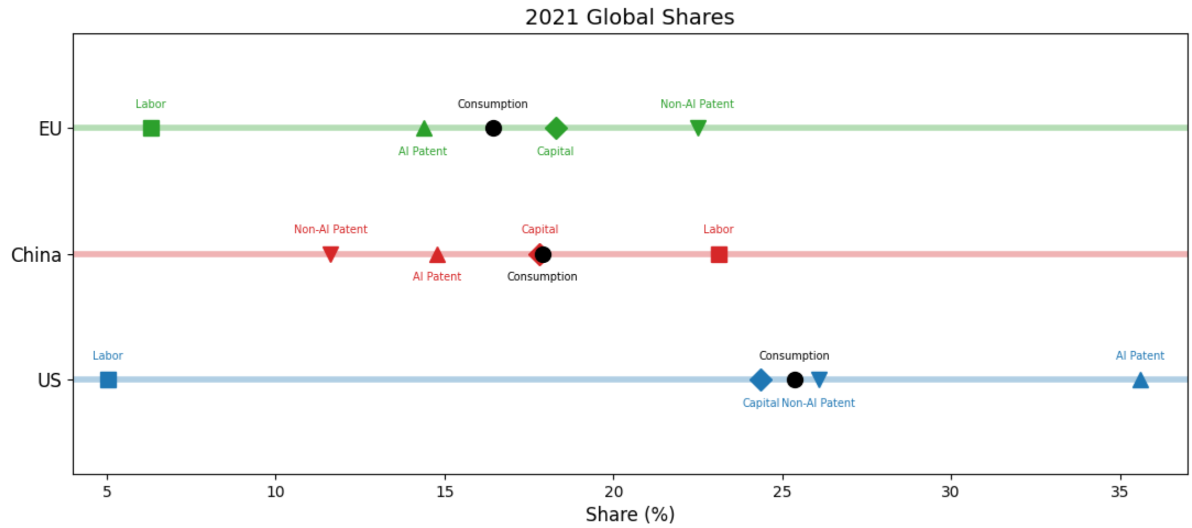


Figure 4.11: Factor and Consumption Shares of Triad in 2021

When the factor share of a country (the position of a marker on its row) lies to the right of its consumption share (the black circle), the country is relatively abundant in that factor and should be a net exporter of it. When a factor lies to the left of consumption, the country is relatively scarce and should be a net importer. The distance between factor and consumption positions indicates the strength of abundance or scarcity. Further, the relative position of AI patents over non-AI patents indicates the relative factor abundance in production. If AI patents lie further to the right of non-AI patents, the country has relatively more abundant AI patents in production. Comparing the two snapshots reveals these shifts in the global distribution of factors.

In 2010, the US showed strong abundance across both patent types. By 2021, while both patent shares declined, AI patents remained substantially to the right of the consumption share. Based on the position, the US can be expected to be a net exporter of goods and services embodying AI-patents. The AI patents remained to the right of non-AI patents, but the gap narrowed, signalling it still maintains relative abundance in AI-patents.

China, on the other hand, had both non-AI patents and AI patents sitting to the far left of its consumption share in 2010, but by 2021, this gap was reduced despite a substantial increase in consumption share. More importantly, AI-patents sit to the right of non-AI patents, signalling that it remains relatively abundant in AI-patents. Another important development has been the catching up of capital stock from the left to almost equal the consumption share. Based on its position in 2021, China can be expected to be a net importer of goods and services embodying AI-patents.

The trajectory of the EU moves in the opposite direction to China. In 2010, the EU showed the right balance of all factors, although relatively speaking, it was still scarce in AI-patents over non-AI patents. But by 2021, the balance deteriorated. AI patents shifted to the left of its consumption share, making it a predicted net importer of goods and services embodying AI-patents. Further, AI patents sit to the left of non-AI patents by a bigger margin, making it relatively even more scarce in AI-patents over non-AI patents.

The visual helps explain why the EU situation is concerning. The gap between AI-patents and the consumption share, along with the other factors of capital stock and non-AI patents, has widened and is currently predicting dependence on imports.

These findings establish that the global distribution of AI knowledge is shifting rapidly, with important implications for international economic relations and for national competitiveness in an AI-driven economy. The question of whether these knowledge endowments translate into trade through comparative advantage mechanisms is addressed in the empirical results that follow.

5
Empirical Results

This chapter presents the empirical results from testing the HOV framework with the four factors and from calculating comparative advantage in AI. Section 5.1 tests whether the factor endowments predict trade patterns according to the HOV framework (RQ 2), using sign tests, rank correlations, and regression analysis to compare measured factor content of trade with predicted factor content as described in Chapter 3.9. Section 5.2 identifies the countries with a comparative advantage in AI patents as of 2021 (RQ 3), using relative factor abundance ratios derived from factor-content calculations. Section 5.3 analyses how comparative advantage positions have evolved from 2010 to 2021, examining both the magnitude and direction of changes along with the relative position of the EU (RQ 4). Section 5.4 presents findings from sensitivity tests of relative factor abundance ratios to any particular industry for China, the US and the EU. Section 5.5 presents findings from robustness checks of relative factor abundance ratios to varying types of patents and depreciation rates. Section 5.6 finally verifies the plausibility of the AI patent findings by verifying if they reflect broader patterns in AI capability. Throughout the chapter, results are interpreted in light of the theoretical framework, methodology, and descriptive findings established in the earlier chapters.

5.1. Testing the HOV Framework: Factor Content of Trade

The first empirical objective is to evaluate whether the HOV framework accurately predicts trade patterns when AI-related and non-AI-related patent stocks are treated as production factors alongside traditional labour and capital. If the framework is valid, the measured and predicted factor contents of trade should closely align. As outlined in Chapter 3.9, three types of tests are conducted to validate this: sign tests, rank correlation tests, and regression analysis.

Table 5.1 reports the results of sign and rank tests at the country level for the period 2010–2021 across all four factors. Overall, the HOV framework performs well. The sign test shows a 90% success rate, indicating that in 9 out of 10 cases, countries are net exporters of the factors in which they are relatively abundant. This high success rate provides robust evidence that factor endowments systematically shape trade flows in the direction predicted by theory. Although slightly below the 0.95 success rate reported by Trefler and Zhu (2010), which focused solely on labour across 41 countries, factor-specific tests (Table 5.2) reveal a 0.92 success rate for labour, closely matching their findings. Consistent with previous studies (Stehrer, 2014; Stöllinger & Guarascio, 2023), the fit for capital is somewhat weaker, mainly due to the lack of consistent industry-level capital stock data across countries. A novel contribution of this research is the strong performance observed for both AI-related and non-AI-related patents, demonstrating that accumulated knowledge stocks influence trade patterns through the same comparative advantage mechanism as traditional production factors.

Table 5.1: Sign and Rank Test Results for all Four Factors by Country, 2010 to 2021

Country Name	Sign Test	(p value)	Rank Correlation	(p value)
All Countries	0.90	(0.00)	0.84	(0.00)
Argentina	0.88	(0.00)	0.93	(0.00)
Australia	0.98	(0.00)	0.80	(0.00)
Austria	1.00	(0.00)	0.72	(0.00)
Belgium	0.88	(0.00)	0.93	(0.00)
Brazil	0.98	(0.00)	0.59	(0.00)
Bulgaria	1.00	(0.00)	0.87	(0.00)
Canada	0.65	(0.03)	0.32	(0.03)
China	0.77	(0.00)	0.87	(0.00)
Croatia	0.75	(0.00)	0.63	(0.00)
Cyprus	0.88	(0.00)	0.49	(0.00)
Czech Republic	0.88	(0.00)	0.92	(0.00)
Denmark	0.90	(0.00)	0.87	(0.00)
Estonia	0.92	(0.00)	0.94	(0.00)
Finland	0.75	(0.00)	0.79	(0.00)
France	0.60	(0.10)	0.14	(0.34)
Germany	1.00	(0.00)	0.85	(0.00)
Greece	0.94	(0.00)	0.57	(0.00)
Hungary	0.75	(0.00)	0.87	(0.00)
India	0.98	(0.00)	0.86	(0.00)
Indonesia	1.00	(0.00)	0.80	(0.00)
Ireland	0.88	(0.00)	0.68	(0.00)
Italy	0.96	(0.00)	0.92	(0.00)
Japan	0.94	(0.00)	0.97	(0.00)
Korea	1.00	(0.00)	0.96	(0.00)
Latvia	0.81	(0.00)	0.78	(0.00)
Lithuania	0.85	(0.00)	0.70	(0.00)
Luxembourg	0.96	(0.00)	0.87	(0.00)
Malta	0.98	(0.00)	0.88	(0.00)
Mexico	0.92	(0.00)	0.96	(0.00)
Netherlands	1.00	(0.00)	0.96	(0.00)
Norway	1.00	(0.00)	0.67	(0.00)
Poland	0.79	(0.00)	0.59	(0.00)
Portugal	0.83	(0.00)	0.47	(0.00)
Romania	0.83	(0.00)	0.87	(0.00)
Russia	0.98	(0.00)	0.96	(0.00)
Saudi Arabia	0.79	(0.00)	0.17	(0.23)

Continued on next page

Country Name	Sign Test	(p value)	Rank Correlation	(p value)
Slovakia	0.96	(0.00)	0.83	(0.00)
Slovenia	0.90	(0.00)	0.88	(0.00)
South Africa	0.94	(0.00)	0.25	(0.08)
Spain	1.00	(0.00)	0.93	(0.00)
Sweden	1.00	(0.00)	0.94	(0.00)
Switzerland	0.77	(0.00)	0.83	(0.00)
Turkey	0.98	(0.00)	0.84	(0.00)
United Kingdom	0.88	(0.00)	0.76	(0.00)
United States	0.98	(0.00)	0.81	(0.00)
Rest of the World	1.00	(0.00)	0.94	(0.00)

The rank test also performs moderately well, achieving an 84% success rate overall. This indicates that not only do measured and predicted factor contents have the same signs, but they also exhibit similar relative magnitudes across factors within countries.

Table 5.2: Sign, Rank and Regression Tests of the HOV Theorem for Individual Factors, 2010 to 2021

	All Factors	Labour	Capital Stock	AI Patents	Non-AI Patents
1. Sign Test	0.90	0.92	0.77	0.93	0.97
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2. Rank Correlation	0.84	0.94	0.61	0.91	0.94
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3. Slope Coefficient	0.34	0.13	0.22	0.45	0.44
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4. R^2	0.71	0.91	0.53	0.85	0.87
Observations	2208	552	552	552	552

The regression results reported in Table 5.2 provide additional perspective on the fit of the HOV framework. For all four factors combined, the slope coefficient is 0.34, with an R^2 of 0.74. These statistics indicate that measured factor content is strongly and significantly correlated with predicted factor content, but the slope is substantially below one. This matches with the pattern highlighted in the literature earlier as the "missing trade" problem by Trefler (1995), and reflects the fact that actual trade flows embed less factor content than the simple HOV model would predict. As discussed in Chapter 3.9, several explanations have been proposed for the missing trade phenomenon. These include the deviations from homothetic preferences (with a change in income consumption share on goods and services changes), and home bias (people in a country tend to consume a larger share of goods and services that are produced at home) (Stehrer, 2014).

The key finding from the regression analysis is that AI patents exhibit a slope coefficient (0.45) very similar to non-AI patents (0.44) and much higher than both labour (0.13) and capital stock (0.22). The R^2 values are also high for both patents, exceeding 0.85, indicating a strong correlation between measured and predicted factor contents. These results, along with the sign and rank tests, further confirm the finding that knowledge endowments measured through patent stocks perform better than traditional factors in predicting trade patterns.

Figure 5.1 visualises the regression relationship between measured and predicted factor content of trade across all countries, factors, and years. The scatter plot shows a clear positive relationship, with data points clustering along a line with a positive slope, confirming the regression results. The missing trade pattern is visible in this plot.

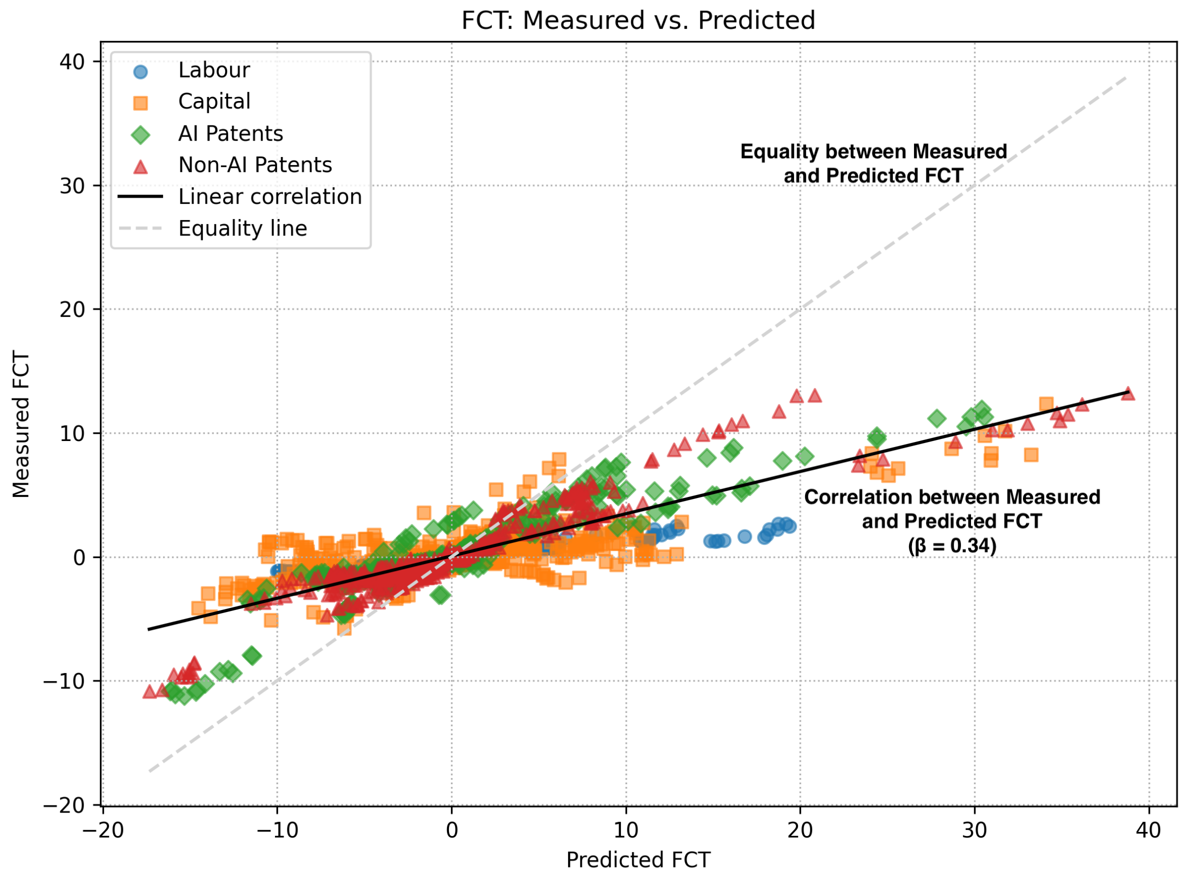


Figure 5.1: Regression correlation between measured and predicted factor content of trade, 2010 to 2021

As described in Chapter 3.11, the deviation from the consumption similarity condition in the HOV framework is examined by calculating the variance of prediction errors at the industry level following the methodology of Trefler and Zhu (2010). Table 5.3 summarises the industries identified with the highest variances across the four factors.

Similar to the findings of Trefler and Zhu (2010), Construction (F), Agriculture (A01), Food (C10T12), and Government (O84) were the sectors containing the largest variance in errors for labour, with consumption in these industries being biased towards domestically produced goods and services. Extending this analysis to other factors showed Real Estate (L) and Government (O84) to have the largest variance for capital stock, Electronics (C26), Media (J59_60) and Health (Q86) to

Table 5.3: Factor-wise Within-industry Highest Mean Variance

Factor	Industry	Mean Variance
Labour	Construction (F)	16.58
	Agriculture (A01)	16.33
	Food (C10T12)	6.69
	Government (O84)	2.94
	Education (P85)	2.51
Capital	Real Estate (L)	1111.60
	Government (O84)	673.66
	Construction (F)	127.69
AI Patents	Electronics (C26)	456.07
	Media (J59_60)	67.99
	Health (Q86)	57.42
	Government (O84)	44.24
	Construction (F)	36.25
Non-AI Patents	Construction (F)	31.52
	Electronics (C26)	15.28
	Pharmaceuticals (C21)	12.70
	Health (Q86)	8.88
	Media (J59_60)	7.41

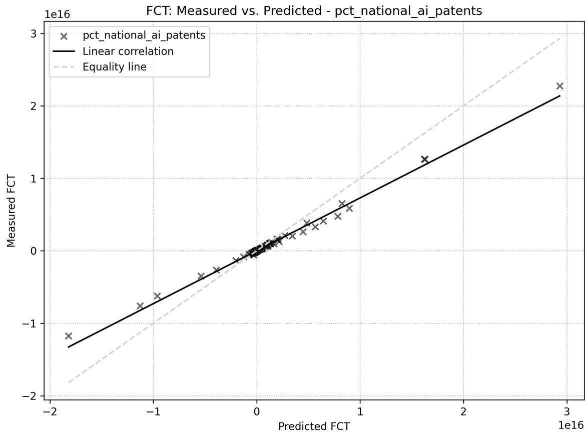
have the largest variance for AI patents, and Construction (F), Electronics (C26), and Pharmaceuticals (C21) to have the largest variance for non-AI patents.

Table 5.4: Sign, Rank and Regression Tests of the HOV Theorem for Individual Factor Excluding their Respective Protected Industries, 2010 to 2021

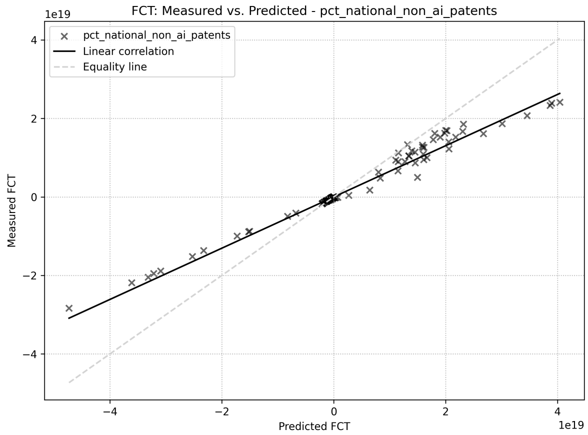
	Labour	Capital Stock	AI Patents	Non-AI Patents
1. Sign Test	1.00	0.93	1.00	0.99
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
2. Rank Correlation	0.99	0.80	1.00	0.96
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
3. Slope Coefficient	0.44	0.75	0.73	0.65
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
4. R^2	0.81	0.93	0.99	0.98
Observations	552	552	552	552

Following the robustness check steps described in Chapter 3.11, the sign, rank, and regression tests are re-conducted after excluding the high variance industries identified in Table 5.3. Table 5.4 summarises these findings. The results show that removing industries where the HOV assumptions are more dominant significantly improves the fit of the HOV framework. Comparing them with our initial results for all industries in Table 5.2, a significant improvement is noticed in all the tests across all four factors. Sign test and rank correlation go to nearly 100% for labour, AI patents and non-AI patents. Regression slope coefficient for capital stock, AI-patents and non-AI patents nearly doubles and gets closer to 1. For labour, while the regression slope coefficient improves from 0.13 to 0.44, it is still far from the improvement achieved by Trefler and Zhu (2010) due to the presence of some outliers, which their study removes from the data.

Figure 5.2 further visualises the improved regression fit for AI and non-AI patents after excluding the protected industries. The near-perfect fit, particularly for AI patents, demonstrates that when consumption similarity holds, patent endowments predict trade patterns with exceptional accuracy. The fact that Electronics (C26) appears among the high-variance industries for both AI and non-AI patents and the fit improves when it is excluded, suggests that this sector has unusual consumption patterns across countries, which stem from a deviation from the assumptions of the HOV framework rather than measurement error.



(a) Regression for AI patents



(b) Regression for Non-AI patents

Figure 5.2: Regression between measured and predicted factor content of trade for patents excluding the protected industries in Table 5.3, 2010 to 2021

Overall, these results address RQ 2 by showing that AI patent stock endowments do indeed predict trade patterns according to the HOV framework, and that accumulated AI knowledge behaves like a factor of production whose abundance or scarcity shapes comparative advantage in internationally traded goods and services.

5.2. Comparative Advantage in AI Patents

Having established that the HOV framework performs well for AI patent endowments, the next step is to identify which countries hold a comparative advantage in AI-related patents. As described in Chapter 3.10, comparative advantage is identified through relative factor abundance ratios, following the approach of Leamer (1980). The descriptive analysis earlier in Section 4.1 showed that five countries dominate global AI patent stocks: the US, EU, China, Japan, and Korea, which together account for approximately 90% of the global total. Table 5.5 calculates relative factor abundance for these five countries as of 2021 using this methodology, showing the ratio of AI to non-AI patents in production, the measured factor content of trade, consumption, and the production-to-consumption ratio that determines relative factor abundance (RFA).

Table 5.5: Relative factor abundance of AI-related patents over non-AI-related patents in top 5 AI-patenting countries, 2021

Country	Production	Net FCT	Consumption	Prod. / Cons.	RFA
CN	0.046	-0.006	0.038	1.207	Yes
KR	0.042	0.063	0.035	1.199	Yes
US	0.049	1.303	0.046	1.075	Yes
JP	0.026	0.027	0.026	1.002	Yes
EU27	0.023	0.009	0.027	0.859	No

The results in Table 5.5 provide clear answers to the question of which countries hold a comparative advantage in AI as of 2021. The US exhibits strong relative abundance in AI patents, with a production-to-consumption ratio of 1.075, meaning that the AI-to-non-AI ratio is approximately 8% higher in production than in consumption. This reveals that the US exports goods and services that embody relatively more AI knowledge than it imports, consistent with comparative advantage.

China and Korea show an even stronger relative abundance, with a production-to-consumption ratio of 1.207 and 1.199 respectively. This indicates that they are producing and exporting goods and services that embody substantially more AI knowledge relative to the general innovative capacity than they consume. China has the highest magnitude of this ratio, suggesting that it has developed a strong specialisation in AI-related technologies and that this specialisation is reflected in its trade patterns.

Japan shows a modest production-to-consumption ratio of 1.002, indicating an approximate balance between AI intensity in production and consumption. The EU stands out as the only entity among the top five that exhibits relative scarcity in AI-related patents, with a production-to-consumption ratio of 0.859, substantially below one. This finding indicates that the EU consumes more AI-intensive goods and services relative to general goods and services than it produces, making it a net importer of AI-related factor content.

Table 5.6: Bilateral relative factor abundance of AI over non-AI patents in the top 5 AI-patenting countries, 2021

Country	Bilateral relative factor abundance
KR	4
CN	3
US	2
JP	1
EU27	0

To assess the robustness of these comparative advantage findings, the bilateral relative factor abundance is calculated following Debaere (2003), as described in Chapter 3.10, in Table 5.6. The pattern matches our earlier findings for the most part from Table 5.5. The only difference is with Korea ranking over China, implying that, looking purely at the ratio of AI-patent endowments over non-AI patent endowments (in production) without accounting for the measured factor content of trade, Korea does slightly better than China.

The comparative advantage results in Table 5.5 answer RQ 3 by identifying the US, China, and Korea as countries holding clear comparative advantage in AI patents as of 2021, Japan as approximately balanced, and the EU as lacking. These findings provide empirical grounding for concerns about European technological competitiveness in AI and raise questions about whether current EU policies and innovation systems are adequate to close the gap with technological leaders.

5.3. Evolution of Comparative Advantage 2010-2021

While the 2021 snapshot provides a current picture of comparative advantage positions, understanding how these positions have evolved is essential for assessing trends and diagnosing whether observed patterns reflect persistent structural features or temporary fluctuations. Figure 5.3 answers RQ 4 by showing the evolution of the relative factor abundance index for AI relative to non-AI patents from 2010 to 2021 for the same five countries examined in Table 5.5.

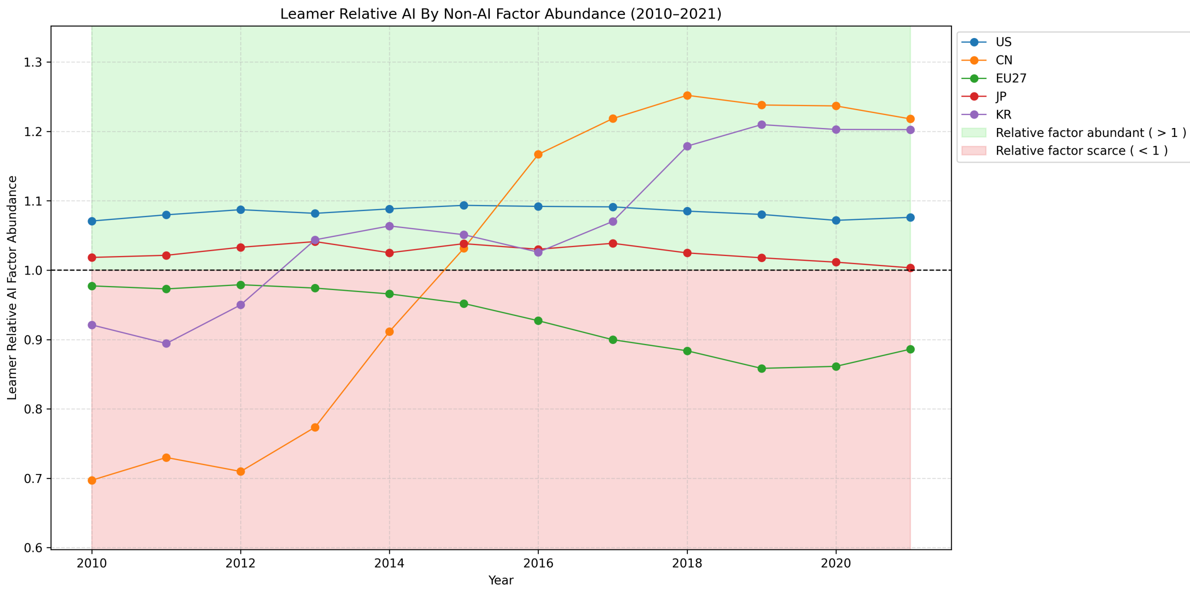


Figure 5.3: Global Relative Factor Abundance Trend, 2010 to 2021

The temporal patterns reveal several important dynamics. The US maintained a comparative advantage in AI throughout the entire period, with its relative factor abundance index remaining more or less consistent above 1. China, on the other hand, began the period with a relative factor abundance index below 1, indicating a lack of comparative advantage in AI relative to non-AI innovation in 2010. However, from 2012 onward, the ratio increased sharply and consistently, reaching 1.2 by 2021. This progression reveals that China has not only accumulated AI patents rapidly, as found in the descriptive results, but has also successfully translated this knowledge accumulation into growing comparative advantage in trade. The inflection point around 2012-2014 coincides with the first major developments around AI and with the beginning of a national push in China to develop AI capabilities (Roberts et al., 2021). Korea shows a similar pattern to China, with a strong comparative advantage emerging around 2014-2015 and strengthening thereafter. The ratio for Japan remained relatively stable and close to unity throughout the period. The trajectory of the EU is the most concerning of the five. The EU began the period with approximate balance, similar to Japan, but unlike Japan, the relative factor abundance ratio declined steadily from 2012 onward. By 2021, the ratio had fallen to 0.86, indicating a lack of comparative advantage. The period of steepest decline, from 2012 to 2019, corresponds precisely to the period when China and Korea were building comparative advantage most rapidly. This suggests that the EU was not simply failing to keep pace with a general global trend toward greater AI specialisation, but was actively losing ground globally.

Figure 5.4 further examines the temporal dynamics within the EU by presenting the same production over consumption ratio for Germany, France, the Netherlands, Sweden, Finland, and Italy, which together account for approximately 85% of EU AI patents. This disaggregation reveals significant heterogeneity in the performance of European countries.

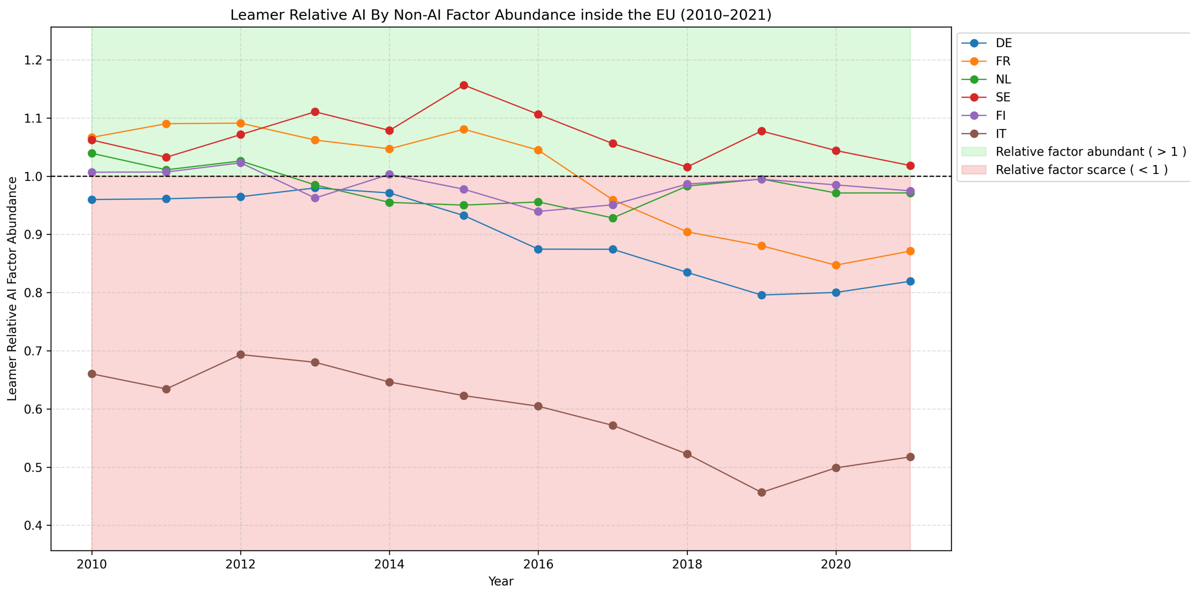


Figure 5.4: EU Relative Factor Abundance Trend, 2010 to 2021

The Netherlands, Sweden, and Finland show this ratio consistently close to 1 throughout most of the period, indicating that these countries have attempted to maintain a comparative advantage in AI. This finding complements the AI intensity trends documented in the descriptive analysis, which showed these countries exhibiting higher AI intensity than the rest of the EU. In contrast, Germany, France, and Italy, the three largest EU economies, show a decline in this ratio below 1 during the period. France fell from above 1 between 2010 and 2015 to below 1 from 2017 onwards, indicating an erosion of comparative advantage. Germany shows a similar pattern, while Italy was always far away. These trends are particularly concerning because these three countries represent the industrial and economic core of the EU. Their failure to maintain a comparative advantage in AI during a period of rapid global AI development undermines the overall technological position of the EU.

5.4. Sensitivity Check

To verify the robustness of the comparative advantage findings, a sensitivity analysis is conducted by recalculating the relative factor abundance for China, the US, and the EU while excluding one industry at a time. As outlined in Chapter 3.11, this approach tests whether the comparative advantage patterns identified in Table 5.5 are strongly driven by any single industry or whether they reflect broader structural characteristics. If the exclusion of a particular industry substantially alters the relative factor abundance ratio substantially, it would suggest that the comparative advantage position is driven disproportionately by that sector rather than representing a general pattern.

The results presented in Table 5.7 are similar to the relative factor abundance results found in Table 5.5, only that in each case an industry is excluded from the calculation. It shows the stability in comparative advantage findings across all industry exclusions. China and the US maintain a relative factor abundance ratio above 1 regardless of which industry is excluded, and the EU shows relative scarcity in all the industry exclusion scenarios, with the ratio remaining fairly close to 0.86.

Table 5.7: Relative Factor Abundance (RFA) Results by Excluded Industry, 2021

Excluded Industry	**China RFA**	**US RFA**	**EU RFA**
Agriculture (A01)	1.204 (Yes)	1.076 (Yes)	0.860 (No)
Forestry (A02)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Fishing (A03)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Mining (B)	1.205 (Yes)	1.077 (Yes)	0.859 (No)
Food (C10T12)	1.204 (Yes)	1.076 (Yes)	0.859 (No)
Textiles (C13T15)	1.212 (Yes)	1.075 (Yes)	0.858 (No)
Wood (C16)	1.207 (Yes)	1.074 (Yes)	0.860 (No)
Paper (C17)	1.203 (Yes)	1.075 (Yes)	0.861 (No)
Printing (C18)	1.207 (Yes)	1.074 (Yes)	0.859 (No)
Petroleum (C19)	1.205 (Yes)	1.075 (Yes)	0.863 (No)
Chemicals (C20)	1.154 (Yes)	1.080 (Yes)	0.874 (No)
Pharmaceuticals (C21)	1.196 (Yes)	1.080 (Yes)	0.870 (No)
Rubber/Plastics (C22)	1.203 (Yes)	1.069 (Yes)	0.863 (No)
Non-Metallic Minerals (C23)	1.207 (Yes)	1.072 (Yes)	0.857 (No)
Basic Metals (C24)	1.194 (Yes)	1.068 (Yes)	0.866 (No)
Fabricated Metals (C25)	1.209 (Yes)	1.072 (Yes)	0.862 (No)
Electronics (C26)	1.173 (Yes)	1.028 (Yes)	0.867 (No)
Electrical Equipment (C27)	1.196 (Yes)	1.067 (Yes)	0.858 (No)

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Excluded Industry	China RFA	US RFA	EU RFA
Machinery (C28)	1.183 (Yes)	1.068 (Yes)	0.869 (No)
Motor Vehicles (C29)	1.202 (Yes)	1.067 (Yes)	0.860 (No)
Other Transport (C30)	1.204 (Yes)	1.071 (Yes)	0.865 (No)
Furniture (C31_32)	1.206 (Yes)	1.072 (Yes)	0.859 (No)
Repair (C33)	1.207 (Yes)	1.074 (Yes)	0.860 (No)
Electricity (D35)	1.205 (Yes)	1.074 (Yes)	0.859 (No)
Water (E36)	1.209 (Yes)	1.075 (Yes)	0.853 (No)
Waste (E37T39)	1.207 (Yes)	1.074 (Yes)	0.860 (No)
Construction (F)	1.216 (Yes)	1.074 (Yes)	0.858 (No)
Motor Vehicle Trade (G45)	1.206 (Yes)	1.074 (Yes)	0.860 (No)
Wholesale (G46)	1.208 (Yes)	1.071 (Yes)	0.865 (No)
Retail (G47)	1.206 (Yes)	1.074 (Yes)	0.860 (No)
Land Transport (H49)	1.206 (Yes)	1.074 (Yes)	0.860 (No)
Water Transport (H50)	1.206 (Yes)	1.074 (Yes)	0.860 (No)
Air Transport (H51)	1.207 (Yes)	1.074 (Yes)	0.860 (No)
Warehousing (H52)	1.206 (Yes)	1.074 (Yes)	0.860 (No)
Postal (H53)	1.207 (Yes)	1.075 (Yes)	0.860 (No)
Accommodation (I)	1.206 (Yes)	1.074 (Yes)	0.859 (No)
Publishing (J58)	1.207 (Yes)	1.074 (Yes)	0.859 (No)
Media (J59_60)	1.262 (Yes)	1.080 (Yes)	0.857 (No)
Telecommunications (J61)	1.216 (Yes)	1.074 (Yes)	0.858 (No)
IT Services (J62_63)	1.208 (Yes)	1.074 (Yes)	0.854 (No)
Financial Services (K64)	1.207 (Yes)	1.074 (Yes)	0.861 (No)
Insurance (K65)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Financial Support (K66)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Real Estate (L)	1.207 (Yes)	1.074 (Yes)	0.860 (No)
Legal/Accounting (M69_70)	1.207 (Yes)	1.073 (Yes)	0.860 (No)
Architecture (M71)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
R&D (M72)	1.207 (Yes)	1.074 (Yes)	0.860 (No)
Advertising (M73)	1.207 (Yes)	1.074 (Yes)	0.857 (No)
Professional Services (M74_75)	1.209 (Yes)	1.077 (Yes)	0.860 (No)
Rental (N77)	1.207 (Yes)	1.074 (Yes)	0.859 (No)
Employment (N78)	1.207 (Yes)	1.074 (Yes)	0.859 (No)
Travel Agency (N79)	1.207 (Yes)	1.075 (Yes)	0.860 (No)
Security (N80T82)	1.208 (Yes)	1.075 (Yes)	0.861 (No)
Government (O84)	1.208 (Yes)	1.075 (Yes)	0.860 (No)
Education (P85)	1.207 (Yes)	1.075 (Yes)	0.860 (No)
Health (Q86)	1.209 (Yes)	1.079 (Yes)	0.859 (No)
Social Work (Q87_88)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Arts (R90T92)	1.208 (Yes)	1.075 (Yes)	0.859 (No)
Sports (R93)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Membership Orgs (S94)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Repair Services (S95)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Personal Services (S96)	1.207 (Yes)	1.075 (Yes)	0.859 (No)

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Excluded Industry	China RFA	US RFA	EU RFA
Households (T)	1.207 (Yes)	1.075 (Yes)	0.859 (No)
Extraterritorial (U)	1.207 (Yes)	1.075 (Yes)	0.859 (No)

The industries whose exclusion produces the largest changes in relative factor abundance ratios differ across countries. For China, the sectors whose exclusion most affects this ratio are Electronics (reduction to 1.173), Chemicals (reduction to 1.154), and Machinery (reduction to 1.183), all of which are major manufacturing sectors. For the US, Electronics (reduction to 1.028) shows the largest effect, indicating that this sector plays an important role for the US. For the EU, the range of variation is narrower, and excluding no industry substantially changes the overall lack of comparative advantage.

These sensitivity results strongly reinforce the main comparative advantage findings and indicate that the identified patterns reflect structural characteristics of knowledge endowments and trade specialisation of each country.

5.5. Robustness Check

The baseline comparative advantage analysis employs PCT patent applications that have entered the national phase, using a 15% depreciation rate to construct knowledge stocks, as described in Chapter 3.4.1 and 3.4.6. As outlined in Chapter 3.11, to assess whether these choices influence the findings, a robustness check is conducted by recalculating the relative factor abundance ratios by varying both the type of patent applications included and the depreciation rate applied. This addresses two concerns: first, whether the exclusion of patents still in the international phase biases the results and second, whether the choice of depreciation rate, which reflects assumptions about knowledge obsolescence, affects the comparative advantage findings.

Table 5.8 reports relative factor abundance ratios for China, the US, and the EU for both patent types (all PCT applications including those in the international phase, and PCT applications entering the national phase) crossed with nine depreciation rates ranging from 0% to 30%.

The results show that the comparative advantage findings remain stable across all specifications. China and the US show relative abundance in all scenarios, while the EU shows relative scarcity. This robustness strengthens confidence in the policy relevance of the findings and suggests that concerns about European competitiveness in AI are grounded in fundamental structural characteristics.

Table 5.8: Relative Factor Abundance (RFA) for Different Patent Types under Alternative Patent Depreciation Rates, 2021

Application Type	Depreciation Rate	China RFA	US RFA	EU RFA
All PCT Applications (including ones in international phase)	0%	1.273 (Yes)	1.049 (Yes)	0.857 (No)
	5%	1.226 (Yes)	1.053 (Yes)	0.853 (No)
	10%	1.191 (Yes)	1.059 (Yes)	0.851 (No)
	12%	1.181 (Yes)	1.061 (Yes)	0.852 (No)
	15%	1.167 (Yes)	1.064 (Yes)	0.852 (No)
	17%	1.160 (Yes)	1.066 (Yes)	0.853 (No)
	20%	1.152 (Yes)	1.069 (Yes)	0.855 (No)
	25%	1.141 (Yes)	1.072 (Yes)	0.857 (No)
	30%	1.134 (Yes)	1.075 (Yes)	0.859 (No)
PCT Applications entering National Phase	0%	1.368 (Yes)	1.063 (Yes)	0.866 (No)
	5%	1.300 (Yes)	1.066 (Yes)	0.859 (No)
	10%	1.246 (Yes)	1.071 (Yes)	0.858 (No)
	12%	1.229 (Yes)	1.072 (Yes)	0.858 (No)
	15%	1.207 (Yes)	1.075 (Yes)	0.859 (No)
	17%	1.195 (Yes)	1.076 (Yes)	0.861 (No)
	20%	1.179 (Yes)	1.078 (Yes)	0.863 (No)
	25%	1.160 (Yes)	1.080 (Yes)	0.866 (No)
	30%	1.146 (Yes)	1.081 (Yes)	0.870 (No)

5.6. Plausibility Check

Before examining the implications of these findings for technological sovereignty strategies of the EU, it is also useful to verify that the patent-based comparative advantage results reflect broader patterns in AI capabilities of the EU. To do this, the analysis draws on the JRC technical report on estimating AI investments in Europe (Nepelski & Sobolewski, 2020), which provides comprehensive data on public and private AI investments across member states. If the AI patent patterns identified earlier for the EU correspond to AI investment patterns in the EU, it strengthens confidence that the comparative advantage findings capture meaningful differences in AI capabilities rather than just patenting behaviour.

The analysis reveals a strong correlation between AI patent stock per capita and total AI investment per capita, with a few outliers. In general, countries with higher per capita investment in AI, such as the Netherlands, Finland, Sweden, and Ireland, also produce higher per capita patent stocks in AI. No attempt is made to establish a causal relationship between these two measures, as this is not the primary objective. Instead, the correlation analysis is used to assess the plausibility of the findings. This alignment suggests that the patent-based comparative advantage measures are somewhat reflective of the underlying differences in AI development efforts across member states. To better understand the outliers, a more granular analysis examines the composition of AI investment across public and private sectors and across different categories, including salaries of ICT specialists, Research and

Development (R&D), and infrastructure. Assuming that patents emerge primarily from private sector activity or public-private collaborations, a second correlation analysis focuses specifically on the relationship between AI patent stock per capita and private AI investment per capita in salaries of ICT specialists, R & D, and computer software and databases (Figure 5.5).

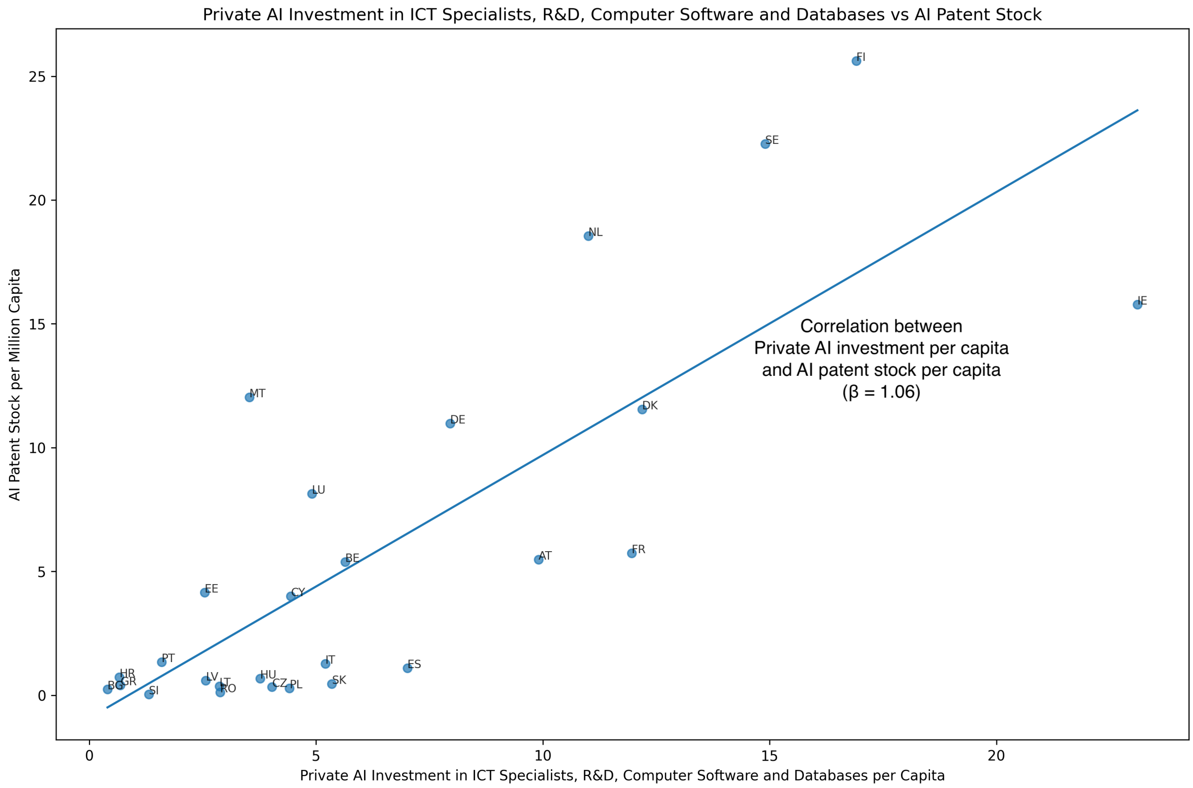


Figure 5.5: Regression correlation between AI patent stock per million capita with private AI investment in salaries of ICT specialists, R&D, Computer Software and Databases per capita, 2018

This refined analysis shows a stronger positive correlation with fewer outliers, confirming that private investment in AI-related human capital and research activities corresponds closely to patent output. France emerges as the most significant outlier, producing only about one-third of the AI patent stock per capita generated by the Netherlands despite having similar levels of private investment per capita. This suggests that investment levels alone do not determine patent productivity and that other factors, such as research quality, technology transfer mechanisms, or industrial structure, also play important roles. Nevertheless, the overall pattern confirms the same internal fragmentation within the EU that emerged from the comparative advantage analysis. Member states differ substantially in both their AI investment levels and their patent outputs, with a small group of Northern European countries leading while larger economies lag.

6
Implications

This chapter interprets the descriptive and empirical findings in light of the technological sovereignty goals of the EU and derives policy-relevant implications and recommendations. Section 6.1 connects the comparative advantage findings to the literature on digital sovereignty, technological dependence, open strategic autonomy, and the EU paradox, examining how reliance of the EU on American and Chinese AI capabilities creates strategic vulnerabilities and analysing the hybrid regulatory approach of the EU in this context. Section 6.2 structures four clear implications from the connections highlighted between the empirical results and the literature, answering RQ 5. Section 6.3 proposes four policy recommendations aligned with these implications, assessing existing EU initiatives and suggesting enhancements to better address the structural challenges revealed by the comparative advantage analysis.

6.1. Technological Dependence, Digital Sovereignty, Open Strategic Autonomy, and the EU Paradox

The empirical findings reveal that the EU does not hold a comparative advantage in AI-related patents relative to its non-AI patents, while the US, China, and Korea maintain or strengthen their AI patent positions. Moreover, the position of the EU deteriorated from 2010 to 2021, as AI became increasingly recognised as a critical technology.

The comparative advantage analysis demonstrates that the EU lacks mastery in AI-related technologies, specialising instead in non-AI technologies while relying on the US and China for AI capabilities. This aligns with Cantner (2023)'s framework, distinguishing "mastery" and "availability" in technological sovereignty, creating vulnerabilities including exposure to higher prices, supply disruptions, and weak bargaining power.

The three dynamics predicted by technology-gap models are evident in the empirical patterns. First, the widening gap: the declining comparative advantage of the EU from 2010 to 2021 occurred while the US and China maintained or improved their positions, consistent with cumulative learning effects in these leading economies. Second, the sectoral patterns suggest deteriorating terms of trade, as the EU retains a comparative advantage in legacy manufacturing (machinery, motor vehicles, electrical equipment) while being a net importer in manufacturing of computers, electronics, and optical products, where over half of AI patents are generated. Third, the erosion of domestic mastery appears in the concentration of EU AI capabilities in a few northern states, with major industrial economies like Germany, France, and Italy showing limited reorientation toward AI.

These findings extend the dependency concerns raised by Caravella et al. (2024) and Guarascio et al. (2025) beyond physical components to encompass the algorithms, models, and intellectual property that define how AI systems operate. As AI becomes embedded in critical infrastructures across healthcare, transportation, finance, and public administration, this dependency represents both an economic disadvantage and a strategic vulnerability. The weak comparative advantage of the EU in AI patents is simultaneously a symptom and a driver of the technological dependence that undermines its technological sovereignty ambitions.

The empirical results also illuminate challenges in operationalising open strategic autonomy as conceptualised by Dupré (2022) and Fabry and Veskoukis (2021). While the framework aims to balance openness with strategic capability, the patent evidence suggests systematic disadvantages in AI. The uneven distribution of capabilities within the EU, with efforts for comparative advantage in AI concentrated in a few northern member states, further complicates coordination efforts. This fragmentation means that even targeted investments or the coordinated plan for "AI made in Europe" discussed by Ulnicane (2022) must overcome substantial internal asymmetries before addressing external competition.

The hybrid strategy of combining normative power (regulatory leadership) with market power (leveraging the internal market) faces a fundamental tension revealed by these findings. The AI Act represents significant normative leadership and has already influenced global AI governance debates. However, regulatory frameworks alone cannot substitute for technological capabilities. The patent evidence suggests that while the EU shapes standards and ethical frameworks, the underlying AI capabilities are increasingly residing outside. From the perspective of Fabry and Veskoukis (2021) and Dupré (2022), strategic autonomy requires not only regulatory tools but also a sufficiently broad industrial and technological base, precisely what the comparative advantage analysis finds lacking.

An important caveat is that the empirical analysis extends only to 2021, providing limited time to observe the effects of EU AI policies implemented between 2018 and 2021. Patent production involves long time horizons from research through application, so these results represent early outcomes rather than definitive assessments of policy impact. Nevertheless, the deteriorating position over the 2010-2021 period occurred precisely when AI was being recognised as strategically critical, suggesting that existing policy responses have not yet reversed underlying trends.

The findings also speak directly to the European Paradox identified by Dosi et al. (2006). The contrast between the strong AI-related scientific output of Europe, documented by Veugelers (2024) and European Commission et al. (2024), and its weak AI patent position reinforces this disconnect between scientific excellence and commercial innovation. The HOV analysis demonstrates that this disconnect has real consequences. Patent endowments significantly shape trade patterns, meaning that failure to convert scientific strength into patentable innovations weakens the competitive position of the EU in global markets.

The report by European Commission (2025f) emphasises that a bottleneck lies in the translation from science to commercial scale-ups. The science base of the EU functions as an under-leveraged asset. Addressing technological sovereignty in AI, therefore, requires moving beyond investment in basic research to tackle the full innovation pipeline, from discovery through patenting, commercialisation, and scaling. The comparative advantage findings suggest that current policies, despite regulatory leadership and scientific strength, have not bridged this gap. As Cantner (2023) mentions, closing technology gaps in GPTs may require investments that deliberately contradict existing comparative advantage, accepting short-term inefficiencies to build long-term capabilities in strategically critical domains.

6.2. Implications for digital sovereignty of the EU

In answer to RQ 5, the empirical findings and their connection with the literature above have four key implications for digital sovereignty strategies of the EU. First, the EU must prioritise developing its computer, electronics, and optical products sector as essential infrastructure for economy-wide AI diffusion, recognising that this sector serves as the primary channel through which AI capabilities flow to all other industries. Second, reducing technological dependence in AI-related intellectual property has become imperative given its pervasive character and the intensifying geopolitical tensions among major powers. Third, addressing the bottleneck in translating research excellence into commercial innovation represents the most immediate opportunity, as the EU maintains strength in AI publications but lags in patents. Fourth, internal divergence in AI capabilities in the EU threatens collective strategic autonomy and requires cohesion-oriented policies to prevent further division. These implications are discussed in detail below.

6.2.1. Prioritisation of computer, electronics, and optical products sector

Empirical findings reveal that the computer, electronics, and optical products sector accounts for over half of all AI patents globally, making it the dominant channel through which AI innovation diffuses into other sectors. This presents a critical challenge for technological sovereignty of the EU because the sector represents precisely where the lack of comparative advantage is most pronounced for the EU. One might reasonably ask why the EU cannot simply accept this specialisation pattern and focus instead on areas where it maintains clear advantages, such as environmental technologies or its legacy manufacturing strengths. The answer lies in understanding the function of AI as a GPT and the mechanisms through which AI capabilities spread throughout an economy.

Consider the automotive sector, where Europe maintains strong patent positions and global leadership. The transition toward autonomous vehicles illustrates how AI dependencies can undermine even established advantages. Despite the

EU holding a comparative advantage in AI patents within the motor vehicles sector itself, European firms are falling behind competitors from China and the US in developing self-driving technology. Companies like BYD and Tesla have established leadership positions not because they possessed superior automotive engineering in traditional terms, but because they could draw on deep capabilities in the computer, electronics, and optics sector to integrate advanced AI systems into vehicles. The diffusion pattern matters a lot here. AI capabilities developed primarily in the computer, electronics, and optics sector flow outward to enable innovations in transportation, manufacturing, healthcare, and other domains. When a region lacks mastery in the originating sector, it struggles to effectively absorb and adapt AI innovations even in sectors where it otherwise possesses strong foundations.

This dynamic creates a compounding vulnerability. The EU cannot simply compensate for weakness in AI core components by focusing on promising new areas like green technologies or environmental innovation. These emerging fields themselves increasingly depend on AI capabilities for optimisation, monitoring, predictive modelling, and control systems. Without a strong foundation in the computer, electronics, and optics sector, the EU risks losing ground not only in AI-intensive emerging industries but also in its traditional strongholds as they undergo AI-driven transformation. Building and investing in this sector is therefore not merely about chasing comparative advantage in one industrial domain. It is about establishing the technological infrastructure necessary for AI to diffuse effectively throughout the entire economy and to maintain competitiveness across existing areas of strength.

6.2.2. Reduction of dependence imperative for AI given pervasive nature and changing geopolitical environment

The comparative advantage analysis demonstrated that the EU relies on the US and China for AI patent stocks and the knowledge they represent. As discussed earlier, this dependency extends beyond physical hardware components to encompass the algorithmic intellectual property that defines how AI systems operate. The significance of this dependency must be understood in light of its pervasive nature.

Unlike previous waves of digital technology, AI is becoming embedded in critical infrastructures spanning healthcare systems, financial services, transportation networks, energy grids, national security, and public administration. The framework provided by Cantner (2023) highlights that technological sovereignty requires both mastery, meaning domestic knowledge and capabilities, and availability, meaning secure access to foreign technology. The current position of the EU reveals growing vulnerability on both dimensions. Limited mastery in core AI technologies reduces the absorptive capacity of the economy and its ability to adapt external innovations to European contexts and needs.

Recent geopolitical developments highlight these risks. The US has demonstrated a willingness to use trade measures and tariffs against European countries to advance its strategic interests. Semiconductor shortages during the COVID-19 pandemic exposed vulnerabilities in supply chains concentrated in specific geographic regions. As strategic competition intensifies among major powers, excessive technological dependence in AI creates leverage points that foreign actors can exploit. The EU faces a fundamental choice. It can continue to pursue a strategy based primarily on regulatory leadership and ethical frameworks while depending on other countries for core AI capabilities. Alternatively, it can commit to building a stronger domestic technological base and supporting the growth of European AI firms capable of competing globally. The changed geopolitical context, combined with the pervasiveness of AI, argues strongly for the latter approach. This does not require complete self-sufficiency or technological autarky, which would be neither feasible nor desirable. It does require developing sufficient mastery and domestic capacity to avoid one-sided dependencies that compromise strategic autonomy.

6.2.3. Immediate opportunity in translating bottleneck from research to commercialisation

The science base of the EU functions as an important but chronically under-leveraged asset. Publication leadership without corresponding patent development and commercial application leaves value on the table and allows other regions to potentially build on European research foundations while capturing the economic and strategic benefits.

Focusing on translation improvements specifically in the computer, electronics, and optics sector offers particular leverage for several reasons. First, as established earlier, this sector serves as the primary channel for AI diffusion throughout the economy. Second, this is precisely where the EU lacks comparative advantage the most, suggesting that targeted interventions could yield substantial marginal returns. Third, a stronger foundation in this sector would enhance absorptive capacity for AI innovations across all other sectors. Addressing this translation bottleneck requires moving beyond investments in basic research to tackle the full innovation pipeline from discovery through commercialisation. This encompasses strengthening university-industry partnerships, improving technology transfer mechanisms, expanding access to scale-up financing for deep-tech startups, creating incentives for talent retention, and building the industrial ecosystems necessary to support AI-intensive firms. The regulatory leadership of the EU and its ability to shape markets through European values represent important assets, but they cannot substitute for capabilities that only emerge through the successful commercialisation of research into products, services, and platforms.

6.2.4. Addressing internal divergence in AI capabilities

The empirical analysis revealed that AI patent intensity and relative factor abundance in AI over non-AI patents vary across EU member states. This fragmentation intensified particularly between 2012 and 2019, coinciding with the rise in AI capabilities of China. The plausibility check using JRC data on AI investments further confirmed these patterns, showing similar internal fragmentation in private AI investment per capita.

These asymmetries create several challenges for EU-level strategy. They complicate coordination and policy-making around AI industrial development because member states have divergent interests based on their different capability levels. They weaken collective bargaining power in international negotiations over AI standards, trade arrangements, and technology governance because the EU cannot speak with one voice from a position of shared strength. They risk creating a further division in Europe in which only some member states develop meaningful AI sovereignty while others remain primarily users of imported technologies, whether from outside the EU or from more advanced member states. Perhaps most fundamentally, they may reduce political support for common initiatives if the benefits are perceived to accrue primarily to a narrow group of already advanced countries.

The EU has long positioned itself as a single economic and political unit in international affairs and has pursued technological sovereignty as a collective rather than national objective. However, achieving this collective sovereignty in AI requires ensuring that the underlying capabilities are distributed broadly enough across member states to support sustained coordination and political commitment. This does not mean that all member states must develop identical AI capabilities or achieve the same levels of patent intensity. It does mean that the gulf between leading and lagging member states must not widen to the point where common strategies become unsustainable. Cohesion and convergence must therefore remain central objectives alongside competitiveness in the EU AI policy. The challenge lies in strengthening AI capabilities in countries that currently lag while simultaneously preserving and enhancing the leadership positions of advanced member states. Success requires creating a broader and more resilient EU-wide AI industrial base that can support the collective technological sovereignty that open strategic autonomy envisions.

6.3. Policy Recommendations for Bridging the AI Gap

This section proposes policy recommendations aligned with the four implications by examining announced EU programs and assessments of whether they are headed in the right direction. It should be noted here that assessing the actual implementation and effectiveness of current initiatives of the EU would require a much more detailed policy analysis beyond the scope of this research. Nevertheless, these recommendations are still useful in getting the right pointers towards technological sovereignty and open strategic autonomy goals of the EU.

6.3.1. Strengthen AI-Enabling Hardware Capabilities

The computer, electronics, and optics sector generates over half of global AI patents and serves as the primary channel for AI diffusion across all other sectors. Without mastery in this foundational layer, European firms risk losing competitiveness even in traditional areas of strength. The European Chips Act is perhaps the biggest step taken by the EU to develop the semiconductor manufacturing capabilities (Wills, 2022). Additionally, Important Projects of Common European Interest (IPCEI) in microelectronics and cloud computing has mobilised several billion euros in aid for companies (European Commission, 2026a). Despite these investments coming a few years too late, they are a step in the right direction. However, these measures remain somewhat narrow in scope and modest in scale when compared to the US and China (Wills, 2022).

Policy could therefore be expanded both in investment scale and scope from a primarily semiconductor-focused approach toward a broader AI hardware strategy. These measures could expand support beyond fabrication to include design, specialised AI accelerators (hardware designed to execute AI workloads faster and more efficiently, like Graphics Processing Units (GPUs)), and advanced sensors. A dedicated European effort on AI chip and system design, building on institutions such as the Interuniversity Microelectronics Centre (IMEC), could target open and interoperable architectures that reduce dependence on non-EU intellectual property. Industrial support could be explicitly tied to building domestic absorptive capacity for AI, through joint research projects and stronger links between AI researchers and electronics manufacturers, so that new hardware investments translate into sustained comparative advantage rather than isolated capacity additions.

6.3.2. Reduce Strategic Dependence in AI Infrastructure, Data, and Intellectual Property

The EU's reliance on non-EU models, platforms, infrastructure, and AI intellectual property creates vulnerabilities for technological sovereignty, particularly as AI becomes pervasive in critical infrastructures. New initiatives for building critical infrastructure, including AI Factories under EuroHPC (European High Performance Computing Joint Undertaking, 2026) and planned AI Gigafactories (European Commission, 2025c), indicate growing recognition by the EU of this challenge. On the data side, the Cloud and AI development act proposal seeks to increase data centre capacity (Marcelin, 2025), and the European Data Union Strategy aims to create high-quality, interoperable European data spaces (European Commission, 2025d). The European Research Council (ERC), European Innovation Council (EIC), and programs such as Horizon Europe have been increasingly funding projects for AI research and intellectual property development (European Commission et al., 2024). However, these initiatives remain an order of magnitude lower compared to the US and China. Just as an example for scale, in 2025 alone, Microsoft announced that it was on track to invest $80 billion in AI-enabled data centres (Smith, 2025).

Given resource constraints and late entry, the EU could choose to focus on areas where its regulatory framework and sectoral strengths provide genuine leverage. Investments in AI infrastructure could prioritise services where European values create distinct advantages, such as privacy-preserving AI and trustworthy data governance. The idea is to basically look at areas both in terms of research and infrastructure that can convert the compliance burden of data protection laws in the EU into a competitive advantage. An advantage of this approach is that these developments can be protected by policies using protectionist measures in the market (Cantner, 2023).

Data, on the other hand, is a constraint that infrastructure and research alone cannot solve. The EU could mandate data contribution requirements from large digital platforms operating in the European markets. Similar to how pharmaceutical companies must share clinical trial data or how financial institutions must report to regulators, platforms above defined thresholds of users or revenue could be required to contribute anonymised datasets to European data commons that researchers and startups can access for AI training. This helps in leveraging the regulatory authority of Europe to create data assets that partially compensate for the lack of European platform giants.

6.3.3. Accelerate the Research-to-Market translation

The coexistence of a strong AI science base and weak AI patenting and commercialisation reflects a structural translation problem rather than isolated gaps. Nagar et al. (2024) provided further evidence showing that while ERC-funded research generated more patent citations and higher quality patents compared to similar European research, US companies derived the greatest benefits from it. They attributed this EU lag to the absence of startup ecosystems and regulatory environments inhibiting new ventures and further recommended that factors such as tech transfer funds and deep tech venture capital can help in the development of this missing ecosystem (Nagar et al., 2024).

Measures that try to address gaps on the ecosystem side include European Digital Innovation Hubs to create supportive innovation ecosystems and services for companies (European Commission, 2025e) and the EIC Accelerator program and the AI innovation package to support European startups and Small and Medium Enterprises (SMEs) (European Commission, 2024, 2026b). For talent and skills, initiatives like the AI Skill Academy try to provide educational and training programs in AI (European Commission, 2025b), while the Talent Pool and the Marie Skłodowska-Curie Action (MSCA) Choose Europe initiatives try attracting and retaining skilled AI talent (European Commission, 2025a). These initiatives make an attempt to address the bottleneck but operate at a budget of hundreds of millions, which is nowhere near the scale needed to fundamentally reshape European innovation systems. They also have different eligibility criteria, application processes, and requirements, making them quite disconnected from each other despite trying to address the same bottleneck. Further, they do not address the venture capital constraint identified by Nagar et al. (2024). Outside of these initiatives, successful national models do exist like the Fraunhofer-Gesellschaft organisation, which operates across 75 institutes and research units, deriving two-thirds of its funding from public and private contracts, fostering entrepreneurial thinking and activities (Fraunhofer-Gesellschaft, 2025a, 2025b).

Newer policies could thus focus on a more coherent innovation pipeline strategy rather than fragmented small-scale programs. These smaller initiatives could be consolidated and scaled around a clearer objective, i.e., converting AI research, especially in the computer, electronics, and optics sector, into patents, startups, and globally competitive firms. This could entail creating significantly larger, outcome-based support for applied AI research centres modelled on successful applied institutes like the Fraunhofer-Gesellschaft or introducing targeted measures for closing the funding gap for AI-intensive firms, perhaps for late-stage startups, to fill in the void left by private venture capital. Regulations could also work towards making it easier for startups to access EU-wide markets instead of having to navigate through different processes for 27 member states.

6.3.4. Promote Convergence in AI capabilities Across Member States

Internal divergence in AI patent intensity and AI investment per capita, with only a small group of Northern European countries building a comparative advantage in AI while major economies and many other members lagging, undermines collective strategic autonomy. The EU has several instruments capable of addressing internal divergence, although they are not specifically designed for AI capacity and capability building. The Recovery and Resilience Facility provides member states with access to funds for digital transformation, favouring countries most affected by COVID-19 (European Commission, 2025g). The New Cohesion Policy provides additional resources for research and innovation in less developed regions (European Commission, 2026c). While these initiatives help in providing resources, they are not designed to systematically close the AI capability gaps.

A positive development in this direction has been the adoption of national AI strategies in 24 of the 27 EU member states, with countries including France, Germany, Austria, Czechia and Denmark updating their strategies to address AI and align with EU-level initiatives (OECD, 2026b). Cohesion policies, however, can be improved to promote structured knowledge transfer. Large EU-funded AI projects could systematically include partners from both leading and laggard member states with clear objectives for joint patenting, shared infrastructures, and researcher mobility. For example, the AI Gigafactories could not be located based solely on looking at the existing computational infrastructure, but could rather be strategically distributed to build capabilities in member states that currently lag. Further, funds promoting the development of AI capacity in lagging regions support isolated projects in these regions aimed at achieving EU goals. These could be enhanced to promote integration of these projects into the European AI value chains. Lastly, policies could support talent circulation schemes, allowing leading AI experts from leading hubs to work part-time or temporarily in emerging centres to help diffuse the capabilities that cannot be achieved by funding alone.

7

Conclusion and Discussion

This chapter synthesises the findings of the thesis and addresses the overarching research question on how the evolution of comparative advantage in AI since 2010 has reshaped the global trade landscape and what the relative position of the EU implies for its ability to achieve technological sovereignty. Section 7.1 concludes with the key empirical findings from the descriptive analysis of AI patent stocks, the HOV framework tests, the comparative advantage rankings and the four main policy implications for EU digital sovereignty strategies, answering the main research question. The section also discusses the contributions of this research to the literature and debates on technological sovereignty. Section 7.2 acknowledges the limitations of this study, including temporal constraints, data imperfections, and measurement challenges. Section 7.4 proposes directions for future research that can further extend and deepen this analysis and Section 7.3 reflects on the thesis journey.

7.1. Conclusion

This thesis examined how the accumulation of AI-related knowledge has shaped the comparative advantage of countries in global trade since 2010 and assessed the implications for the EU to achieve technological sovereignty. By integrating AI-related and non-AI-related patent stocks alongside labour and capital stock endowments into an extended HOV framework, the research addressed a fundamental question about which countries possess the knowledge capital underpinning AI as an emerging GPT and whether these endowments translate into measurable trade advantages.

The descriptive analysis established that AI has emerged as a distinct technological domain, with AI intensity rising across countries after 2014. However, the global distribution of AI knowledge is highly concentrated, with the US, China, Japan, Korea, and the EU accounting for nearly 90% of global AI patent stocks. Within this leading group, the position of the EU has deteriorated markedly. The share of the EU in global AI patents declined by approximately 9 percentage points between 2010 and 2021, a steeper fall than observed for non-AI patents. This indicates that Europe is not simply losing ground in innovation overall but is falling behind faster in what may prove to be the most economically consequential technology of the coming decades. The AI intensity of the EU as of 2021 stands at only 2.5%, roughly half the level of the US, China, and Korea.

The empirical tests of the HOV framework yielded two important findings. First, the factor-content approach successfully predicts trade patterns when knowledge capital, measured through patents, is incorporated alongside traditional production factors. Sign tests achieved 90% success rates across all four factors, meaning that in 90% of cases, countries are net exporters of factors in which they are relatively abundant. Rank tests achieved 84% success rates, and regression analyses showed strong correlations between measured and predicted factor content of trade. Second, and more novel, AI-related and non-AI-related patents performed better than labour and capital in explaining trade patterns. This finding validates accumulated knowledge stocks as meaningful formable factors that shape comparative advantage through the same mechanisms operating for traditional production factors.

The comparative advantage analysis revealed that as of 2021, the US, China, and Korea hold a clear comparative advantage in AI patents relative to non-AI patents, while the EU does not. The relative factor abundance ratio for AI patents stood at 1.076 for the United States, 1.218 for China, and 1.203 for Korea, but only 0.886 for the EU. Values above 1 indicates that the production ratio of goods and services embodying AI over non-AI patents is more than the consumption ratio. This implies that the EU consumes relatively more goods and services embodying AI patents than it produces. Within the EU, only the Netherlands, Sweden, and Finland maintained or attempted to build a comparative advantage in AI, while Germany, France, and Italy lost ground.

The temporal analysis showed that the relative position of the EU deteriorated most sharply between 2012 and 2019, coinciding precisely with the rapid rise in AI capabilities of China and with growing internal fragmentation among EU member states. The US maintained a consistent comparative advantage throughout the period, while the EU moved in the opposite direction, from approximate balance to a clear lack of advantage.

Industry-level analysis revealed that the computer, electronics, and optics sector generates nearly 50% of global AI patents and serves as the primary channel through which AI capabilities diffuse into other sectors. The weakness of the EU in this foundational layer creates compounding vulnerabilities. Even in sectors where Europe maintains traditional strengths, such as automotive manufacturing, the integration of AI technologies increasingly depends on capabilities concentrated in the computer, electronics, and optics sector. Without mastery in core AI components, European firms risk losing competitiveness across multiple domains as AI-driven transformation accelerates.

The empirical findings demonstrate that the EU lacks a comparative advantage in the knowledge stocks underpinning AI and that this has worsened over time. This pattern creates strategic vulnerabilities as AI becomes embedded in critical infrastructures spanning healthcare, finance, transportation, energy, and public administration. Increasing reliance of the EU on the US and China for AI-related models, algorithms, and intellectual property exposes it to risks of supply disruptions, unfavourable pricing, and reduced bargaining power. In a changing geopolitical environment where strategic competition intensifies among major powers, excessive technological dependence in AI creates leverage points that foreign actors can exploit.

The research identified four key policy implications. First, the EU must prioritise developing its computer, electronics, and optics sector as essential infrastructure for economy-wide AI diffusion, recognising that AI capabilities developed in this sector flow outward to enable innovations across all other industries. Second, reducing technological dependence in AI-related intellectual property has become imperative given its pervasive character and mounting geopolitical tensions. Third, addressing the bottleneck in translating research excellence into commercial innovation represents the most immediate opportunity, as the EU maintains strength in AI publications but lags in patents and commercialisation. Fourth, internal divergence in AI capabilities threatens collective strategic autonomy and requires cohesion-oriented policies to prevent further division in Europe in AI development.

This thesis contributes to international trade theory by demonstrating that formable knowledge factors measured through accumulated patent stocks shape comparative advantage through mechanisms analogous to those operating for traditional production factors. The successful application of the HOV framework to AI-related patents validates the use of this approach for analysing technological specialisation in emerging GPTs. The research extends the HOV literature by incorporating AI-specific knowledge stocks as distinct from broader innovative capacity and by broadening geographic coverage to include China alongside comparisons between the EU and the US. For policy, it provides the first empirical assessment systematically linking AI patent endowments to comparative advantage and technological sovereignty, offering data-grounded evidence that regulatory leadership of Europe must be complemented by strengthened technological capabilities to achieve genuine strategic autonomy in the AI era.

7.2. Limitations

Several limitations of this research merit acknowledgement. First, the analysis extends through 2021 due to data constraints on capital stocks and the time lag required for PCT applications to enter the national phase. This endpoint precedes major developments in generative AI following the release of ChatGPT in late 2022 and provides a limited window to capture the effects of EU AI policies implemented between 2018 and 2021. Given the long time horizons involved in research, innovation, and patenting cycles, the results represent early outcomes rather than definitive assessments of policy impact. Future research extending the analysis through 2023 or 2024 would capture more recent shifts in AI capabilities and policy effectiveness.

Second, the construction of capital stock endowments required substantial imputation due to the incomplete availability of industry-level net capital stock data across all countries. While the imputation strategy employed comparison countries with similar economic characteristics and rescaled estimates to match observed aggregate totals, measurement error in the capital factor remains higher than for labour or patents. Since capital serves primarily as a control variable rather than the central focus of the analysis, this limitation does not fundamentally undermine the main findings regarding AI patent comparative advantage. Nevertheless, improved capital stock data would strengthen the robustness of the HOV tests.

Finally, the use of patent stocks as the primary measure of AI knowledge capital carries inherent limitations. Not all innovations are patented, and patenting propensities vary across countries, industries, and technological domains. Some AI innovations may be protected through trade secrets, first-mover advantages, or rapid deployment rather than through formal intellectual property rights. Patent counts also do not capture variation in the quality or economic value of individual patents. While the research addressed some of these concerns by using PCT applications entering the national phase that signal a stronger commercial intent and by constructing stocks that weight recent patents more heavily, patents remain an imperfect measure of innovative capacity. Complementary indicators such as AI-related publications, venture capital investments, or AI talent concentrations could provide additional perspectives on knowledge endowments, though these alternative measures face their own limitations regarding comparability and availability at the industry level.

7.3. Reflection

The primary objective of this research was to empirically assess the position of the EU in the global race for AI by analysing its comparative advantage against key trade partners, particularly the US and China. The HOV factor-content framework was adopted using AI-related patents as a crucial measure of knowledge capital. The successful alignment of the measured factor content of trade with the predicted content for AI and non-AI patents demonstrated that this approach provides a meaningful and empirically sound source of comparative advantage. This finding validates the use of patents as a strong indicator of technological capability in emerging GPTs like AI.

The research process highlighted several significant roadblocks. A major constraint was the choice of the patent indicator itself. While many different avenues exist for patent selection, such as using the country of the inventor, country of the applicant, or filings at national offices, data availability for consistent, cross-country, and industry-level analysis ultimately constrained the study. The decision to use PCT applications entering the national phase, while standard, acknowledged under-representing Chinese patent activity and that this would minimally affect the calculation of the relative factor abundance.

A second major difficulty was obtaining comprehensive, industry-level net capital stock data, which was essential as a control factor for the HOV analysis. The absence of fully consistent data across all countries and industries required the application of extensive imputation and aggregation strategies, which inevitably introduced a risk of estimation errors in the capital factor calculations.

Despite these hurdles, the work generated key methodological and empirical contributions. It not only addressed the core research problem of positioning the EU but also involved the creation of a new, aggregate, and cleaned dataset at the country-industry level for all factors - AI patents, non-AI patents, net capital stock, and labour. This process required developing specific methodologies and Python scripts to automate the cleaning, imputation, and aggregation of disparate data sources into a single, comprehensive file for the HOV calculation.

Finally, the research presented some difficulties in the final stage of connecting the rigorous empirical findings with concrete policy implications. The quantitative result that the EU, as an aggregate, lacks a comparative advantage in AI patents and is internally fragmented is clear. However, translating this quantitative lag into specific, actionable policy advice for achieving technological sovereignty required a focused analysis to bridge the gap between economic theory and political strategy.

7.4. Future Work

The current research provides a foundation for understanding comparative advantage in AI that can be extended in several directions. First, the factor decomposition approach applied to patents could be extended to labour and capital endowments. Industry-level labour could be divided into employees working on AI-relevant tasks, such as AI specialists, machine learning engineers, and data scientists, and those in non-AI-relevant tasks. Net capital stock could be decomposed into AI-specific capital, including specialised computing infrastructure, data centres, and AI software platforms, and general capital. This three-dimensional decomposition across AI and non-AI variants of labour, capital stock, and patent stock would enable much more granular analysis of comparative advantage and provide a clearer diagnosis of which specific factor endowments drive the AI capability gap in the EU. Such analysis would follow the methodology established by Stöllinger and Guarascio (2023) for digital tasks and ICT capital but extend it to the AI domain with greater specificity.

Second, future research could attempt to integrate complementary assets, including data availability and computing infrastructure, as additional factors in the HOV framework. Productivity gains from AI depend heavily on access to large datasets for training models and on computational resources for running complex algorithms. Quantifying country-level and industry-level endowments of data assets and computing capacity would provide a more complete picture of the full set of factors driving AI-related trade patterns. While measurement challenges exist, proxy indicators such as data centre capacity, cloud computing investment, or digital platform usage could capture variation in these complementary assets across countries. Incorporating these factors would test whether the lack of comparative advantage of the EU in AI patents extends to or is partially offset by strengths in data or infrastructure endowments.

Third, extending the temporal coverage through 2023 or 2024 would capture the effects of generative AI developments and recent policy interventions. The period following 2021 has witnessed rapid advances in LLMs that have accelerated AI adoption across sectors. Analysing whether these developments have altered comparative advantage patterns or whether they have reinforced existing concentrations of AI capabilities would provide important insights. Additionally, a few years of implementation of EU AI policies, including the AI Act, Chips Act, and various innovation support programs, would by then have elapsed, enabling more robust assessment of policy effectiveness in closing capability gaps.

Finally, future work could move beyond general policy recommendations and focus on the specific directives and actions stemming from the AI policy of the EU. The goal can be to map these policy actions onto the empirical findings to determine which interventions are most effective in helping member states build comparative advantage and which are not. This work could aim to create assessment feedback loops, allowing policymakers to quantitatively evaluate the trade and factor content impact of their strategies, ensuring that the EU is not steering in a strategically or economically incorrect direction.

References

Abramovitz, M. (1956). Resource and output trends in the United States since 1870. *American Economic Review*, *46*(2), 5–23.

Archibugi, D. (2001). Pavitt's taxonomy sixteen years on: A review article. *Economics of Innovation and New Technology*, *10*(5), 415–425. https://doi.org/10.1080/10438590100000016

Bernhofen, D. M., & Brown, J. C. (2005). An empirical assessment of the comparative advantage gains from trade: Evidence from Japan. *American Economic Review*, *95*(1), 208–225. https://doi.org/10.1257/0002828053828491

Boeing, P., & Mueller, E. (2019). Measuring China's patent quality: Development and validation of ISR indices. *China Economic Review*, *57*, 101331. https://doi.org/10.1016/j.chieco.2019.101331

Bonfiglioli, A., Crinò, R., Filomena, M., & Gancia, G. (2025). *Comparative advantage in ai-intensive industries: Evidence from us imports* (Working Paper No. 11642). CESifo Working Paper Series, Center for Economic Studies and ifo Institute (CESifo), Munich. https://www.ifo.de/DocDL/cesifo1_wp11642.pdf

Bowen, H. P., Leamer, E. E., & Sveikauskas, L. (1987). Multicountry, multifactor tests of the factor abundance theory. *American Economic Review*, *77*(5), 791–809.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies: 'Engines of growth'? *Journal of Econometrics*, *65*(1), 83–108. https://doi.org/10.1016/0304-4076(94)01598-T

Brown, S. A. (2024). Beyond the great firewall: Eu and us responses to the china challenge in the global digital economy. *Journal of European Integration*, *46*(7), 1089–1110. https://doi.org/10.1080/07036337.2024.2402752

Burhan, M., Singh, A. K., & Jain, S. K. (2017). Patents as proxy for measuring innovations: A case of changing patent filing behavior in Indian public funded research organizations. *Technological Forecasting and Social Change*, *123*, 181–190. https://doi.org/10.1016/j.techfore.2016.04.002

Burnay, M., & Circiumaru, A. (2023). The AI global order: What place for the European Union? In M. Egan, K. Raube, J. Wouters, & J. Chaisse (Eds.), *Contestation and polarization in global governance* (pp. 264–281). Edward Elgar Publishing. https://doi.org/10.4337/9781800887268.00022

Calcara, A., Teer, J., & Zaccagnini, I. (2025). Technological underpinnings of european autonomy and us-china competition. *Journal of European Integration*, *47*(6), 943–963. https://doi.org/10.1080/07036337.2025.2536828

Cantner, U. (2023). Industrial policy and technological sovereignty. In S. Tagliapietra & R. Veugelers (Eds.), *Sparking Europe's new industrial revolution: A policy for net zero, growth and resilience* (pp. 71–88, Vol. 33). Bruegel.

Caravella, S., Crespi, F., Cucignatto, G., & Guarascio, D. (2024). Technological sovereignty and strategic dependencies: The case of the photovoltaic supply chain. *Journal of Cleaner Production*, *436*, 140586. https://doi.org/10.1016/j.jclepro.2023.140222

Chor, D. (2010). Unpacking sources of comparative advantage: A quantitative approach. *Journal of International Economics*, *82*(2), 152–167. https://doi.org/10.1016/j.jinteco.2010.07.004

Cockburn, I. M., Henderson, R., & Stern, S. (2018). *The impact of artificial intelligence on innovation* (Working Paper No. 24449). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w24449

Cohen, E. (1992). *Le Colbertisme high-tech: Économie des télécom et du grand projet* (Sciences Po Economics Publications (main) No. hal-03573071). HAL.

Creemers, R. (2025). The regulation of generative AI in China. In *The Oxford handbook of AI governance*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198940272.013.0039

Davis, D. R., & Weinstein, D. E. (2001). An account of global factor trade. *American Economic Review*, *91*(5), 1423–1453. https://doi.org/10.1257/aer.91.5.1423

Davtyan, T. (2025). The U.S. approach to AI regulation: Federal laws, policies, and strategies explained. *Case Western Reserve Journal of Law, Technology & the Internet*, *16*(1), 223–277.

Debaere, P. (2003). Relative factor abundance and trade. *Journal of Political Economy*, *111*(3), 589–610. https://doi.org/10.1086/374179

Dosi, G., Llerena, P., & Sylos Labini, M. (2006). The relationships between science, technologies and their industrial exploitation: An illustration through the myths and realities of the so-called 'European paradox'. *Research Policy*, *35*(10), 1450–1464. https://doi.org/10.1016/j.respol.2006.09.012

Dupré, B. (2022). *European sovereignty, strategic autonomy, Europe as a power: What reality for the European Union and what future?* (Policy Paper No. 620). Fondation Robert Schuman. Paris, France.

Edler, J., Blind, K., Kroll, H., & Schubert, T. (2023). Technology sovereignty as an emerging frame for innovation policy: Defining rationales, ends and means. *Research Policy*, *52*(6), 104765. https://doi.org/10.1016/j.respol.2023.104765

European Central Bank. (2026). Euro foreign exchange reference rates.

European Commission. (2020). Shaping Europe's digital future. https://doi.org/10.2759/48191

European Commission. (2021). Proposal for a regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts.

European Commission. (2024). AI innovation package.

European Commission. (2025a). AI talent, skills and literacy.

European Commission. (2025b). DIGITAL-2025-SKILLS-08-GENAI-ACADEMY-STEP: Sectoral digital skills academies — digital skills academy in GenAI.

European Commission. (2025c). EU launches InvestAI initiative to mobilise €200 billion of investment in artificial intelligence.

European Commission. (2025d). European data union strategy.

European Commission. (2025e). European digital innovation hubs (EDIHs).

European Commission. (2025f). *The future of European competitiveness: Part A — a competitiveness strategy for Europe*. Publications Office of the European Union. Luxembourg. https://doi.org/10.2872/1823372

European Commission. (2025g). Recovery and resilience facility.

European Commission. (2026a). Background information for important projects of common European interest (IPCEI).

European Commission. (2026b). EIC accelerator.

European Commission. (2026c). Regional policy 2021–2027 (New cohesion policy).

European Commission, Directorate-General for Research and Innovation, & Group of Chief Scientific Advisors. (2024). *Successful and timely uptake of artificial intelligence in*

science in the EU. Publications Office of the European Union. https://doi.org/10.2777/46863
European High Performance Computing Joint Undertaking. (2026). AI factories.
Eurostat. (2025). Macroeconomic globalisation indicators based on FIGARO (2025 edition).
Eurostat. (2026a). Cross-classification of fixed assets by industry and by asset (stocks) (NAMA_10_NFA_st).
Eurostat. (2026b). National accounts employment data by industry (up to NACE A64).
Fabry, E., & Veskoukis, A. (2021). *Strategic autonomy in post-Covid trade policy: How far should we politicise supply chains?* (IAI Papers No. 21|33). Istituto Affari Internazionali. Rome, Italy.
Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, *105*(10), 3150–3182. https://doi.org/10.1257/aer.20130954
Felten, E. W., Raj, M., & Seamans, R. (2018). A method to link advances in artificial intelligence to occupational abilities. *AEA Papers and Proceedings*, *108*, 54–57. https://doi.org/10.1257/pandp.20181021
Fleming, L., King, C., & Juda, A. I. (2007). Small worlds and regional innovation. *Organization Science*, *18*(6), 938–954. https://doi.org/10.1287/orsc.1070.0289
Fraunhofer-Gesellschaft. (2025a). About Fraunhofer.
Fraunhofer-Gesellschaft. (2025b). Finances.
Freeman, C. (Ed.). (1986). *Design, innovation and long cycles in economic development*. Design Research Publications.
Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*(4), 1661–1707.
Guarascio, D., Holzner, M., Iacobucci, D., & Meliciani, V. (2025). European competitiveness in the new global context: Structural constraints, strategic dependencies and the role of the new industrial policy. *Journal of Industrial and Business Economics*, *52*(3), 525–533. https://doi.org/10.1007/s40812-025-00368-x
Hahn, F. H., & Matthews, R. C. O. (1964). The theory of economic growth: A survey. *The Economic Journal*, *74*(296), 779–902. https://doi.org/10.2307/2228848
Hakura, D. S. (2001). Why does HOV fail? The role of technological differences within the EC. *Journal of International Economics*, *54*(2), 361–382. https://doi.org/10.1016/S0022-1996(00)00096-9
Heckscher, E. F. (1919). The effect of foreign trade on the distribution of income. *Ekonomisk Tidskrift*, *21*, 497–512.
Johnson, D. K. N. (2002). *The OECD technology concordance (OTC): Patents by industry of manufacture and sector of use* (tech. rep. No. 2002/05). OECD Publishing. Paris. https://doi.org/10.1787/521138670407
Katila, R. (2000). Using patent data to measure innovation performance. *International Journal of Business Performance Management*, *2*(1/2/3), 180–194. https://doi.org/10.1504/ijbpm.2000.000072
Labaj, M., & Majzlíková, E. (2023). L-M compilation of employment data for FIGARO 2022 database. https://doi.org/10.17632/gzp7rh25g7.1
Lach, S. (1995). Patents and productivity growth at the industry level: A first look. *Economics Letters*, *49*(1), 101–108. https://doi.org/10.1016/0165-1765(94)00618-c
Leamer, E. E. (1980). The Leontief paradox, reconsidered. *Journal of Political Economy*, *88*(3), 495–503.
Leamer, E. E. (1984). *Sources of international comparative advantage: Theory and evidence*. MIT Press.

Leontief, W. (1953). Domestic production and foreign trade: The American capital position re-examined. *Proceedings of the American Philosophical Society*, *97*(4), 332–349.
Li, X. (2012). Behind the recent surge of Chinese patenting: An institutional view. *Research Policy*, *41*(1), 236–249. https://doi.org/10.1016/j.respol.2011.07.003
Lybbert, T. J., & Zolas, N. J. (2014). Getting patents and economic data to speak to each other: An 'Algorithmic links with probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, *43*(3), 530–542. https://doi.org/10.1016/j.respol.2013.09.001
Marcelin, T. J. M. (2025). Cloud and AI development act.
Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., Walsh, T., Hamrah, A., Santarlasci, L., ... Oak, S. (2025). The ai index 2025 annual report. *CoRR*, *abs/2504.07139*. https://doi.org/10.48550/arXiv.2504.07139
Nagar, J. P., Breschi, S., & Fosfuri, A. (2024). ERC science and invention: Does ERC break free from the EU paradox? *Research Policy*, *53*(8), 105038. https://doi.org/10.1016/j.respol.2024.105038
Nepelski, D., & Sobolewski, M. (2020). *Estimating investments in general purpose technologies: The case of AI investments in Europe* (JRC Technical Report No. EUR 30072 EN). Publications Office of the European Union. Luxembourg. https://doi.org/10.2760/506947
North, D. C., & Thomas, R. P. (1973). *The rise of the Western world: A new economic history*. Cambridge University Press. https://doi.org/10.1017/cbo9780511819438
OECD. (2009). *OECD patent statistics manual*. https://doi.org/10.1787/9789264056442-en
OECD. (2025). Trade in employment (TiM) database.
OECD. (2026a). OECD employment database.
OECD. (2026b). OECD.AI policy observatory: National dashboards.
OECD. (2026c). STAN: OECD structural analysis database.
Office for National Statistics. (2025). Capital stocks and fixed capital consumption, UK: 2025.
Ohlin, B. (1924). *Handelns teori* [Doctoral dissertation, Stockholms Högskola].
Pavitt, K. (1984). Sectoral patterns of technical change: Towards a taxonomy and a theory. *Research Policy*, *13*(6), 343–373. https://doi.org/10.1016/0048-7333(84)90018-0
Peneder, M. (2016). Competitiveness and industrial policy: From rationalities of failure towards the ability to evolve. *Cambridge Journal of Economics*, *41*(3), 829–858. https://doi.org/10.1093/cje/bew025
Reiner, C., & Stöllinger, R. (2025). Europe's quest for technological sovereignty: A feasible path amidst global rivalries.
Research Institute of Economy, Trade and Industry, Hitotsubashi University, & Peking University Growth Lab. (2023). CIP database 2023.
Reserve Bank of India. (2026). KLEMS database.
Ricardo, D. (1817). *On the principles of political economy, and taxation*. Cambridge University Press. https://doi.org/10.1017/cbo9781107589421
Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2021). The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *AI & Society*, *36*(1), 59–77. https://doi.org/10.1007/s00146-020-00992-2
Romer, P. M. (1996). Why, indeed, in America? Theory, history, and the origins of modern economic growth. *The American Economic Review*, *86*(2), 202–206.
Rosenberg, N. (1983). *Inside the black box: Technology and economics*. Cambridge University Press. https://doi.org/10.1017/cbo9780511611940

Schankerman, M., & Pakes, A. (1986). Estimates of the value of patent rights in European countries during the post-1950 period. *The Economic Journal*, *96*(384), 1052–1076. https://doi.org/10.2307/2233173

Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, *53*(7), 1113–1126. https://doi.org/10.1287/mnsc.1060.0624

Schumpeter, J. A. (1950). The process of creative destruction. In *Capitalism, socialism and democracy* (3rd ed., pp. 81–86). Allen; Unwin.

Smith, B. (2025). The golden opportunity for American AI.

Soete, L. (1987). The impact of technological innovation on international trade patterns: The evidence reconsidered. *Research Policy*, *16*(2–4), 101–130. https://doi.org/10.1016/0048-7333(87)90026-6

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, *39*(3), 312–320. https://doi.org/10.2307/1926047

Stehrer, R. (2014). *Does the home bias explain missing trade in factors* (wiiw Working Paper No. 110). Vienna Institute for International Economic Studies (wiiw). Vienna.

Stöllinger, R., Foster-McGregor, N., Holzner, M., Landesmann, M., Pöschl, J., & Stehrer, R. (2013). *A 'Manufacturing imperative' in the EU – Europe's position in global manufacturing and the role of industrial policy* (Research Report No. 391). Vienna Institute for International Economic Studies (wiiw). Vienna.

Stöllinger, R., & Guarascio, D. (2023). Comparative advantages in the digital era: A Heckscher–Ohlin–Vanek approach. *International Economics*, *175*, 63–89. https://doi.org/10.1016/j.inteco.2023.05.002

Stöllinger, R., & Guarascio, D. (2024). Assessing digital leadership: Is the EU losing out to the US? *Open Economies Review*, *36*(2), 329–371. https://doi.org/10.1007/s11079-024-09772-7

Stöllinger, R., & Landesmann, M. (2020). The European Union's industrial policy. In *The Oxford handbook of industrial policy* (pp. 621–660). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198862420.013.23

Svensson, R. (2015). *Measuring innovation using patent data* (IFN Working Paper No. 1067). Stockholm, Research Institute of Industrial Economics (IFN).

Swiss Federal Statistical Office. (2026). Capital stock statistics.

Tortoriello, M. (2015). The social underpinnings of absorptive capacity: The moderating effects of structural holes on innovation generation based on external knowledge. *Strategic Management Journal*, *36*(4), 586–597. https://doi.org/10.1002/smj.2228

Trefler, D. (1993). International factor price differences: Leontief was right! *Journal of Political Economy*, *101*(6), 961–987.

Trefler, D. (1995). The case of the missing trade and other mysteries. *American Economic Review*, *85*(5), 1029–1046.

Trefler, D., & Zhu, S. C. (2010). The structure of factor content predictions. *Journal of International Economics*, *82*(2), 195–207. https://doi.org/10.1016/j.jinteco.2010.07.006

Ulnicane, I. (2022). Artificial intelligence in the European Union: Policy, ethics and regulation. In T. Hoerber, G. Weber, & I. Cabras (Eds.), *The Routledge handbook of European integrations*. Routledge. https://doi.org/10.4324/9780429262081-19

Vanek, J. (1968). The factor proportions theory: The N-factor case. *Kyklos*, *21*(4), 749–756. https://doi.org/10.1111/j.1467-6435.1968.tb00141.x

Veugelers, R. (2024). An innovation-based industrial policy for the EU. *Intereconomics*, *59*(5), 254–261. https://doi.org/10.2478/ie-2024-0052

Wang, Y., & Li, J. (2017). ICT's effect on trade: Perspective of comparative advantage. *Economics Letters*, *155*, 96–99. https://doi.org/10.1016/j.econlet.2017.03.022

Wills, S. (2022). A tale of two "Chips" acts. *Optics and Photonics News*, *33*(11), 26–33. https://doi.org/10.1364/opn.33.11.000026

World Bank. (2026). World development indicators.

World Intellectual Property Organization. (2025a). PATENTSCOPE artificial intelligence index.

World Intellectual Property Organization. (2025b). PATENTSCOPE: WIPO's global patent search system.

Zúñiga, N., Burton, S. D., Blancato, F., & Carr, M. (2024). The geopolitics of technology standards: Historical context for us, eu and chinese approaches. *International Affairs*, *100*(4), 1635–1652. https://doi.org/10.1093/ia/iiae124

A

Usage of AI

AI tools were used in a limited and supportive manner during the preparation of this report, primarily to improve the clarity and quality of academic writing. Grammarly and the built-in Overleaf paraphrasing functionality were used to correct grammatical structures and refine sentence-level expression. In addition, ChatGPT was used selectively to improve writing flow in some sections, without altering the underlying meaning or introducing new substantive content.

AI tools were not used to generate original analyses, empirical findings, interpretations, or conclusions. All analytical choices, methodological decisions, interpretations of results, and recommendations presented in this report were developed independently through my own reasoning and academic judgment. I take full responsibility for the content, accuracy, and conclusions of this report.

Lastly, AI was used to generate the cover image of this report based on the prompt cited below in Section A.1. Overall, AI tools were used solely as writing support instruments with recognised limitations, and not as substitutes for independent academic work.

A.1. AI References

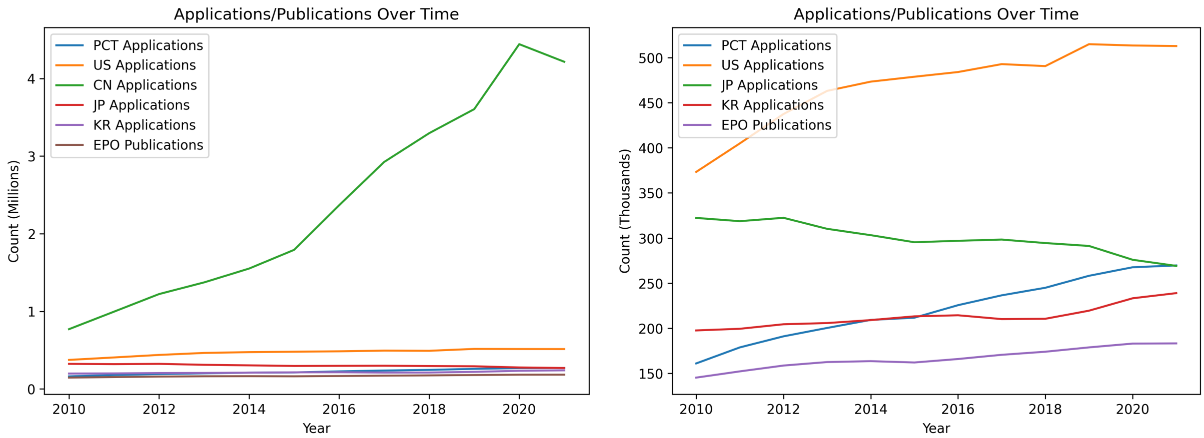
ChatGPT (2026). Cover image request. https://chatgpt.com/share/6980a908-e460-8000-8cc8-794043450895

B

Comparison of Patent Indicators

Before constructing the patent stock measures used in the main analysis, this appendix assesses the reliability and potential biases of alternative patent indicators. We compare patent filings across major national patent offices of the US, China, Japan, Korea, and the EPO, alongside total PCT applications filed at WIPO to motivate the use of PCT applications entering the national phase as the primary indicator.

Figure B.1 shows patent filing trends from 2010 to 2021. Chinese patent applications grew by more than 400% over this period, far outpacing other patent offices. In contrast, filings at the US, Korean, and European Patent Offices increased by only 20–35%, while Japan experienced a decline. This divergence is particularly pronounced after 2013.



(a) Patent Filings

(b) Patent Filings without China

Figure B.1: Patent Filings Trend

The extraordinary growth in Chinese patent filings is well documented and largely reflects institutional incentives rather than proportional increases in underlying innovative activity. Prior research shows that government subsidy programs and policy targets emphasising patent quantity encouraged strategic and low-quality patenting (Boeing & Mueller, 2019; Li, 2012). Consistent with this interpretation, China's patent grant rate is approximately 20%, compared to ~60% in the United States, Japan, and the European Union. Despite the low grant rate, the sheer volume of applications means that China still grants more patents in absolute terms than any other country.

By contrast, PCT applications filed at WIPO grew by 67% over the same period. Excluding China, PCT trends closely mirror those observed in the US and Europe (B.1b), suggesting that PCT data provide a reasonable proxy for innovative activity in most regions. The relative under-representation of China in the PCT system reflects the higher costs of international filing and the prevalence of domestically oriented or lower-value applications that never enter the PCT process.

These patterns have important implications for indicator choice. Measures based on national patent office filings would be heavily skewed toward China, conflating institutional incentives with genuine technological progress. PCT applications entering the national phase offer a more balanced alternative: they filter out lower-quality applications, reduce home-country bias, and align closely with innovation trends in advanced economies.

For this study, the under-representation of China in PCT data is unlikely to distort the main results. Comparative advantage is measured using the relative abundance of AI-related patents over non-AI-related patents within countries. Any downward bias in Chinese patent counts should affect both categories similarly, leaving relative specialization largely unchanged. Consistent with this, AI intensity measures derived from Chinese national filings and from Chinese PCT applications are very similar.

Overall, while PCT data understate the absolute level of Chinese patenting, they provide a quality-adjusted and internationally comparable measure of innovative activity. If anything, the use of PCT data likely yields conservative estimates of China's comparative advantage in AI, implying that the results may understate rather than exaggerate China's technological position.

C

AI and non-AI Patent Identification

This appendix documents the procedure used to identify AI-related and non-AI-related patent applications using the WIPO PATENTSCOPE database. The objective is to construct a comprehensive dataset of PCT applications that have entered the national phase in at least one national patent office, and to disaggregate these applications into AI-related and non-AI-related patents.

C.1. Scope of Patent Data

We focus on PCT patent applications that satisfy the following criteria:

- The application date lies between 2000 and 2021
- The applicant residence corresponds to a given country (identified by standard country codes)
- The application is filed under the PCT system (office code **WO**)
- The application has entered the national phase in at least one national patent office

Requiring national phase entry ensures that the patents reflect inventions with a credible intention to seek protection beyond the international filing stage.

C.2. PATENTSCOPE Fields Used

Patent records are retrieved and filtered using the following PATENTSCOPE fields:

- **AD** (Application Date): used to restrict applications to the 2000–2021 period
- **ARE** (Applicant Residence): used to assign patents to countries
- **OF** (Office Code): set to **WO** to identify PCT applications
- **NPCC** (National Phase Country Code): used to ensure that the application has entered the national phase in at least one patent office
- **CPC** (Cooperative Patent Classification): used for technology-based identification of AI patents

- **IC** (International Patent Classification): used as an additional technology filter
- **EN_TI**, **EN_AB**, **EN_CL**: English-language title, abstract, and claims, used for keyword-based identification of AI-related content

C.3. Identification of Total PCT Patents

For each country, total PCT patent applications are identified using a PATENTSCOPE query that combines:

- the application date restriction
- applicant residence
- PCT filing status
- national phase entry in at least one national patent office

C.4. Identification of AI-related Patents

AI-related patents are identified following the methodology of the WIPO PATENTSCOPE AI Index (World Intellectual Property Organization, 2025a). Two complementary query segments are used:

1. **Segment 1**: Identification based on a detailed list of AI-specific CPC codes covering machine learning, neural networks, intelligent control systems, computer vision, speech processing, robotics, and related technologies.
2. **Segment 2**: Identification based on a combination of IPC and CPC codes together with extensive keyword searches applied to english titles, abstracts, and claims. Keywords capture both core AI techniques (e.g. machine learning, deep learning, neural networks) and application domains (e.g. autonomous vehicles, medical imaging, fintech, smart cities).

Both segments impose the same restrictions on application date, applicant residence, PCT filing status, and national phase entry as used for total patent identification. The set of AI-related patents is constructed as the union of patents retrieved by Segment 1 and Segment 2 queries.

C.5. Identification of non-AI-related patents

A Python-based data script consolidates patents across all countries and years. The script:

- aggregates the total PCT patents
- merges AI-related patents obtained from the union of Segment 1 and Segment 2 queries
- computes non-AI patent counts by removing AI-related patents from the total PCT patents

D

Figaro Country Codes

This appendix documents the country codes used in the FIGARO IIO Tables. These same country codes have used in our analysis and figures.

D.1. EU-27 Countries

Table D.1 lists the FIGARO country codes and labels for the 27 Member States of the European Union.

Table D.1: FIGARO EU-27 Country Codes

Code	Country
AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
EL	Greece
ES	Spain
FI	Finland
FR	France
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia

D.2. Non-EU Countries

Table D.2 reports the FIGARO country codes for selected non-EU economies along with the rest of the world.

Table D.2: FIGARO Non-EU Countries and Aggregated Regions

Code	**Country**
AR	Argentina
AU	Australia
BR	Brazil
CA	Canada
CH	Switzerland
CN	China
ID	Indonesia
IN	India
JP	Japan
KR	South Korea
MX	Mexico
NO	Norway
RU	Russia
SA	Saudi Arabia
TR	Turkey
UK	United Kingdom
US	United States
ZA	South Africa
FIGW1	Rest of the World

E

Figaro Industry Codes

This appendix describes the industry classification used in the FIGARO IIO Tables. Industries are classified according to NACE Revision 2 (Statistical Classification of Economic Activities in the European Community). FIGARO aggregates selected NACE divisions into composite sectors, which are denoted by combined codes (e.g. C10T12, J62_63). These same industry codes have used in our analysis and figures and are presented below in Table E.1.

Table E.1: FIGARO Industry Codes (NACE Rev. 2)

Code	**Industry**
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B	Mining and quarrying
C10T12	Manufacture of food products; beverages and tobacco products
C13T15	Manufacture of textiles, wearing apparel, leather and related products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31_32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment

Continued on next page

Code	Industry
D35	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply
E37T39	Sewerage, waste management, remediation activities
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58	Publishing activities
J59_60	Motion picture, video, television programme production; programming and broadcasting activities
J61	Telecommunications
J62_63	Computer programming, consultancy, and information service activities
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L	Real estate activities
M69_70	Legal and accounting activities; activities of head offices; management consultancy activities
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74_75	Other professional, scientific and technical activities; veterinary activities
N77	Rental and leasing activities
N78	Employment activities
N79	Travel agency, tour operator and other reservation service and related activities
N80T82	Security and investigation, service and landscape, office administrative and support activities
O84	Public administration and defence; compulsory social security
P85	Education
Q86	Human health activities
Q87_88	Residential care activities and social work activities without accommodation

Continued on next page

Code	**Industry**
R90T92	Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities
R93	Sports activities and amusement and recreation activities
S94	Activities of membership organisations
S95	Repair of computers and personal and household goods
S96	Other personal service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies

F
Code Appendix

This appendix provides documentation of the scripts used to construct the labour, capital, patent, and factor content of trade datasets employed in this thesis. All scripts are written in Python and are organised into four primary directories corresponding to these four data categories. The scripts follow a systematic numbering convention with each numbered script performing a smaller chunk of operation that is used by the script with the next numbered. In each directory initial scripts are generally focused on data preparation and cleaning operations, while subsequent scripts focus more on analytical computations and generate visualisations. The complete repository is available at https://github.com/nikhil-megh/ca_in_ai. The repository is currently private and will be made publicly available following the publication of the associated research paper.

F.1. Labour Scripts

The labour directory contains eight Python scripts that process employment data from multiple sources to construct industry-level labour endowments for 45 countries and rest of the world over the period 2010–2021, following the methodology by (Labaj & Majzlíková, 2023).

The data processing workflow begins with script `1_transform_TIM.py`, which transforms the TIM database from long format to a structured panel format suitable for analysis. This script standardises country and industry codes to ensure consistency with the Figaro classification system. Script `2_Figaro_IO_Update.py` updates the latest 2025 edition Figaro input-output tables to exclude the data of Albania, Montenegro, North Macedonia, and Serbia, as they are not part of our analysis.

Script `3_labor_consolidation_2022_recreate.py` follows the methodology by (Labaj & Majzlíková, 2023) to recreate the flow for producing the final labour files as was created by them. This is used to produce the core script `4_labor_consolidation_2025.py`. This script merges employment data from TIM with Figaro industry classifications, impute missing values using industry-level patterns, and reconcile discrepancies between data sources. It incorporates the most recent updates to both datasets. Script `5_labor_WDI_employment.py` integrates aggregate country-level employment totals from the World Development Indicators to validate and adjust the industry-disaggregated employment figures.

The final three scripts generate summary statistics and visualisations. Script `6_la` bor_summary.py produces descriptive statistics including employment levels by country and industry, growth rates, and coverage statistics. The visualisation scripts 7_labour_country_visuals.py and 8_labour_industry_visuals.py generate comparative figures showing employment distributions across countries and industries, respectively, and temporal trends in employment composition.

F.2. Capital Scripts

The capital data directory comprises twelve scripts that construct capital stock estimates at the industry and country level for the same 45 countries and rest of the world over the period 2010–2021.

Three preliminary scripts prepare the source data. Script 0_filter_OECD_STAN_data.py filters the OECD STAN database to extract relevant variables and ensure consistency with the Figaro industry classification. The scripts 0_pivot_OECD_STAN_data.py, 0_pivot_pwt_data.py, and 0_pivot_pwt_data_figw1.py reshape the data from long to wide format, with separate pivoting operations for OECD STAN and PWT data to facilitate subsequent imputation procedures.

The capital stock imputation is executed through three sequential scripts. Script 1_capital_stock_impute_bucket1.py implements the first imputation, which uses capital intensity of countries whose industry level net capital stock data is available to estimate missing capital stock observations for industries of other countries where it is unavailable. The 2_capital_stock_impute_CN.py script applies a specialised imputation procedure for China. The 3_capital_stock_impute_bucket2.py script performs a second round of imputation for remaining missing values.

The 4_capital_stock_validate.py script conducts diagnostic tests on the imputed capital stock series, comparing estimated values against available benchmarks and checking for internal consistency. The 5_capital_factor_vector.py script transforms the validated capital stock data into factor endowment vectors suitable for use in the factor content of trade calculations.

The final three scripts produce summary statistics and visualisations. The 6_capital_summary.py script generates descriptive statistics on capital stocks and capital intensity across countries and industries. The 7_capital_country_visuals.py and 8_capital_industry_visuals.py scripts create comparative visualisations of capital stock endowments across countries and industries, respectively.

F.3. Patent Scripts

The patent data directory contains seventeen scripts that process patent application data from the WIPO PATENTSCOPE database to construct AI-related patents, construct patent stocks with appropriate depreciation adjustments, and aggregate patent holdings by country and industry.

Script 0_initial_descriptives.py loads patent data from multiple patent offices (PCT, USPTO, EPO, JPO, KR, CN) and creates time series visualisations comparing PCT application volumes with national office filings and grant rates. Script 1_patent_consolidation.py consolidates individual country patent files into a unified database, extracting IPC4 codes and standardising identifiers while removing duplicates. Script 2_ai_patent_consolidation.py processes AI-specific patent data from WIPO's two query segments (CPC-based and keyword-based) and merges them into a single AI patent dataset.

Script 3_patent_and_ipc_weights.py calculates patent weights (inverse of applicant count per patent) and IPC4 weights (inverse of IPC4 code count per patent) for fractional allocation. Script 4_patent_country_year_aggregate.py aggregates weighted patent counts by applicant residence country and application year. Script 5_patent_industry_aggregate.py maps patents to NACE Rev.2 industries using the IPC-to-ISIC concordance following Lybbert and Zolas (2014), applying fractional weights across multiple technology-industry assignments.

Scripts 6_non_ai_count_country.py and 7_non_ai_count_industry.py compute non-AI patent counts by subtracting AI patents from total PCT patents at country and industry levels, respectively. Scripts 8_patent_stock_country.py and 9_patent_stock_industry.py apply the perpetual inventory method with 15% annual depreciation to construct patent stocks from application flows for country-year and country-industry-year observations.

Script 10_patent_country_summary_tables.py generates descriptive statistics tables for patent stocks and flows aggregated by country. Script 11_patent_industry_summary_tables.py produces summary tables for patent data disaggregated by industry. Scripts 12_patent_country_visuals.py and 13_patent_industry_visuals.py create visualisations of patent stocks, growth rates, and AI intensity by country and industry, respectively.

Scripts 14_ai_patent_factor_vector.py and 15_non_ai_patent_factor_vector.py transform AI and non-AI patent stock data into factor requirement matrices compatible with the FIGARO IIO structure for FCT calculations. Script 16_patent_depreciation_robustness.py recalculates patent stocks under alternative depreciation rates to test sensitivity of results to the baseline 15% assumption.

F.4. Factor Content of Trade Scripts

The FCT directory contains 43 scripts implementing the theoretical framework for computing factor content of trade, conducting statistical tests of factor proportions theory, and performing robustness checks.

Scripts `0_us_china_eu_2010.py` and `0_us_china_eu_2021.py` create focused visualisations of factor shares for the US, China, and the EU for benchmark years 2010 and 2021. Script `0_factor_shares.py` visualises the distribution of factor cost shares in value added across countries and time.

Script `1_gross_output.py` extracts gross output by country-industry from FIGARO IIO tables and aggregates across all years into a single file. Script `2_value_added.py` similarly extracts value added by country-industry from FIGARO tables for all years. Script `3_net_trade_vector.py` computes net export vectors for each country-industry-year combination from FIGARO bilateral trade flows.

Script `4_factor_vector.py` assembles the complete factor endowment matrix by stacking AI patents, non-AI patents, labour, and capital data for each country-industry-year, normalised by gross output to obtain the factor vector.

Script `5_leontief_inverse.py` computes the technical coefficients matrix A from FIGARO IIO data and calculates the Leontief inverse $L = (I - A)^{-1}$ for each year. Script `5_leontief_validity_check.py` verifies that the computed Leontief inverse satisfies the identity $A \cdot L = L \cdot A = L - I$ as a diagnostic check.

Script `6_measured_fct.py` computes measured factor content of trade using equation $f^c = e' \cdot L \cdot T^c$, where e' is factor vector, L is the Leontief inverse, and T^c is the net trade vector for country c.

Script `7_shares.py` computes countries' consumption shares σ^c from GDP and trade balance data for use in predicted FCT calculations. Script `8_factor_endowments.py` aggregates industry-level factor data to construct country-level factor endowment vectors V^c.

Script `9_predicted_fct.py` computes predicted factor content of trade using the Vanek equation $\tilde{F}^c = V^c - \sigma^c V^W$ for each country and year. Script `10_eu_fct_agg.py` aggregates measured FCT, predicted FCT, and consumption shares across EU27 member states to treat the EU as a single economic entity.

Script `11_factor_wise_fct.py` decomposes factor content calculations by individual factors, computing sign consistency between measured and predicted values for each factor separately. Script `12_fct_tests.py` implements sign tests, rank tests, and regression analysis following Trefler (1995) to evaluate HOV model performance aggregated across all countries. Script `12_fct_tests_country_level.py` performs the same tests disaggregated by individual country.

Script `13A_single_factor_abundance_PCT_ALL.py` computes single-factor abundance measures for all PCT applications. Script `13B_relative_factor_abundance_PCT_ALL.py` calculates relative factor abundance indices comparing AI to non-AI patents following Leamer (1980).

Scripts `13C_single_factor_abundance_PCT_NATIONAL.py` and `13D_rela tive_factor_abundance_PCT_NATIONAL.py compute the same abundance measures but do this for PCT applications that have entered national phases. Scripts 14A_plot_single_factor_abundance_PCT_All.py, 14B_plot_relative_factor_abundance_PCT_ALL.py, 14C_plot_single_factor_abundance_PCT_NATIONAL.py, and 14D_plot_relative_factor_abundance_PCT_NATIONAL.py generate corresponding time series visualisations of these abundance measures.

Script 15_patent_investment_comparasion.py compares AI patent per capita with AI investment per capita in the EU for plausibility.

Script 16_fct_robustness_test.py re-estimates baseline HOV tests for patent stocks calculated with different depreciation rates. Scripts 17_rfa_robustness_all.py and 18_rfa_robustness_national.py recalculate relative factor abundance under alternative depreciation rates for all PCT applications and PCT applications entering national phase, respectively. Script 18_rfa_robustness_agg_2021.py produces a summary table comparing relative factor abundance values for 2021 across all depreciation rate specifications.

Script 19_fct_sensitivity_calculations.py implements sensitivity analysis by excluding each of the 64 industries in turn and recalculating factor vectors, Leontief inverse, net trade vectors, and measured FCT for each specification. Script 20_fct_sensitivity_eu_agg.py aggregates EU27 countries for each industry-exclusion sensitivity specification.

Scripts 21_fct_sensitivity_rfa_tests.py and 21_fct_sensitivity_rfa_tests_combine.py compute relative factor abundance for each industry-exclusion specification and compile results across all 64 sensitivity tests to assess robustness. Script 22_fct_sensitivity_treffler_tests.py implements industry-variance decomposition tests following the methodology of Trefler and Zhu (2010). Script 23_fct_sensitivity_non_tradable_tests.py tests improvements of the HOV fit by re-running the HOV tests after removing the high-variance industries.

F.5. Computational Environment

All scripts require Python 3.8 or higher with the following key dependencies: NumPy (1.21+), pandas (1.3+), matplotlib (3.4+), scipy (1.7+), and statsmodels (0.13+). Additional requirements are specified in the requirements.txt file in the repository root directory. The scripts assume a Unix-like file system structure and require modification of hard-coded file paths to execute in alternative computing environments.