Institutional Configurations and China–EU Collaborative Patenting Intensity

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Institutional Configurations and China–EU Collaborative Patenting Intensity:

An Exploratory Quantitative Analysis of Innovation-Relevant Institutional Frictions in the European Union

Master's thesis

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I, Jingsong Yang, hereby declare that I have completed this Master's Thesis independently. All ideas, data, and sources used have been properly acknowledged and referenced.

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Abstract

This study explores how configurations of innovation-relevant institutional conditions in the 27 EU member states are associated with the intensity of China–EU collaborative patenting between 2016 and 2022. Using an exploratory quantitative descriptive cross-sectional design and relying exclusively on publicly available data, the analysis employs hierarchical cluster analysis (Ward's method) on five targeted institutional dimensions- intellectual property rights protection, R&D tax incentives, state aid openness, FDI screening strictness, and industrial policy alignment with Chinese strategic sectors- together with bivariate associations, configurational cross-tabulations, and supplementary regression.

Four distinct institutional profiles emerge. Stronger IPR protection and greater industrial policy alignment show consistent positive associations with collaborative patenting intensity (CPI). The combination of high IPR protection and high policy alignment is associated with the highest mean CPI, while configurations involving high state aid and strict screening show substantially lower levels. Economic development indicators display negligible associations. These patterns suggest that specific institutional combinations, rather than general economic scale, shape observable non-equity knowledge integration. The study contributes to institutional duality and OLI frameworks by treating co-inventor patents as a proxy for light-asset entry mode, particularly highlighting the complementarity between strong IPR protection and industrial policy alignment.

Keywords: collaborative patenting, institutional configurations, IPR protection, industrial policy alignment, China–EU innovation cooperation, FDI screening

CERCS: S180, S186, S190

Introduction

1.1 Research Background

Europe's innovative R&D capabilities have always been of interest to Chinese companies, especially in the last decade. Many of them seek access to advanced technology and knowledge. The European Union has strong innovation ecosystems with universities, research centres, and technology clusters. But the level of technology cooperation between Chinese and EU inventors varies quite a bit across EU countries. Some member states show much more joint patent activity than others.

These differences cannot be fully explained by market size or general economic factors alone. It is reasonable to infer that specific institutional conditions, such as intellectual property rights and R&D support, may play a role. This study examines the relationship between these conditions and collaborative patent patterns. Due to the lack of detailed firm-level data and the minimal changes in many institutional indicators over time, this study employs an exploratory quantitative descriptive cross-sectional approach.

1.2 Research Problem

Many previous studies have focused on foreign direct investment (FDI) or broad institutional distances, but this often faces two problems. First, aggregate FDI data fails to reflect the micro-processes of knowledge sharing (Kostova, 1999). Second, broad governance indicators change slowly over time and tend to overlook specific policy areas affecting technological cooperation, such as intellectual property enforcement or R&D tax rules.

This study addresses these problems by focusing on observable co-inventor patents and using only publicly available indicators relevant to innovation. This means that this study employs a descriptive, exploratory, and cross-sectional design aimed at discovering empirical patterns rather than proving causality. Its goal is simply to describe how institutional conditions in EU member states cluster and to explore whether specific configurations are systematically associated with the intensity of co-inventor patents.

1.3 Research Questions

The main research question is:

What configurations of innovation-related institutional conditions in EU member states are associated with variation in the intensity of China-EU collaborative patenting?

Two exploratory sub-questions are:

How do EU member states cluster in terms of their innovation-policy institutional profiles?

Are specific institutional configurations systematically associated with higher or lower levels of China-EU collaborative patenting intensity?

1.4 Research Scope

This study covers all 27 EU member states. Data cover the period 2016 to 2022 and are averaged to handle limited year-to-year changes in institutional variables. For FDI screening (FDS), the average uses only 2020- 2022 data to reflect the post-2019 EU framework implementation more accurately. This temporal structure reflects the post-2019 EU FDI screening framework; sensitivity checks using a 2020–2022-only window are reported in Section 4.5. The outcome variable is defined in Section 2.1 and operationalized in Section 3.4. The condition variables come from public sources: Heritage Foundation Property Rights, OECD R&D Tax Incentives Database, EU State Aid Scoreboard, European Commission FDI Screening Reports, and the Industrial Policy Database. Rather than testing isolated linear effects of individual institutional variables, the analysis uses a configurational approach that examines how combinations of conditions associate with collaborative patenting intensity.

1.5 Structure of the Thesis

The thesis is divided into five chapters. Chapter 1 presents the introduction and research questions. Chapter 2 reviews existing research findings. Chapter 3 describes the data and methodology. Chapter 4 presents descriptive results and discussion. Chapter 5 summarises the main findings, discusses their theoretical and policy implications, points out the limitations of the research, and proposes future research directions.

To systematically identify the relevant institutional conditions and build the empirical analysis on existing theoretical foundations, the next chapter reviews the literature on cross-border knowledge integration, institutional frictions, and collaborative patenting as a non-equity entry mode.

Literature Review

This section first defines key concepts, then presents theoretical foundations, and finally reviews empirical evidence to show the research gap.

2.1 Definition of Core Concepts

Cross-border knowledge integration refers to the collaborative development of new ideas by inventors and institutions from different countries. To quantify this integration, a clear and measurable indicator is co-invention patents—patents jointly owned by at least one Chinese inventor and at least one inventor from an EU country. OECD data show that such co-inventions reflect international collaboration in the inventive process (OECD, 2026). This study uses collaborative patenting intensity as a proxy because it is based on publicly available patent records and does not require confidential information at the firm level.

Innovation-relevant institutional frictions refer to differences in rules and policies between different countries, which can increase or decrease the cost of participating in transnational innovation activities. Broad indicators measuring institutional distance, such as the Worldwide Governance Indicators, often include areas like political stability that may not directly affect technology cooperation (Kaufmann et al., 2010). In contrast, this study focuses on five more targeted areas: strength of intellectual property rights protection, generosity of R&D tax incentives, openness of state aid for innovation, strictness of FDI screening, and alignment of industrial policy priorities. These areas are more directly related to strategic asset seeking and knowledge flows.

Collaborative patenting intensity is measured as the average number of China-EU co-inventor patent families per million population. This normalisation allows comparison across countries of different sizes. The measure comes from OECD patent statistics (EPO, USPTO, and PCT data) and focuses on patents with foreign co-inventors. Higher intensity suggests stronger observable collaboration in invention activities.

Most studies treat patent activity as an indicator of innovation output- a result of R&D investment (Basche, 2021; LaBelle et al., 2024). This is an effective and widely used approach. However, the meaning of patents differs when the focus shifts to how companies in emerging economies acquire strategic assets overseas. For Chinese firms seeking technology in the EU, patents are not only R&D outcomes but also potential strategic tools for entering foreign innovation networks with low asset commitment. This study therefore repositions co-inventor patents filed at the EPO, USPTO, or under the PCT as a proxy for light- asset entry mode.

In the literature on strategic asset seeking, patents and trademarks have been identified as explicit targets of Chinese cross-border mergers and acquisitions (Wang et al., 2024). While acquiring patents through equity investment (mergers and acquisitions) is a common approach, joint patent applications represent another non-equity route to achieve the same goal. Chinese companies do not need to acquire companies that own patents; instead, they can achieve their objectives by co-inventing with European partners and jointly applying for patents. This involves less asset investment and is subject to less FDI screening.

To demonstrate this repositioning of CPI, the following sections will place the analysis within the framework of entry mode theory and the broader literature on non-equity modes. Entry mode theory provides a methodological framework. The research of Naghavi and Leahy (2006) shows that host country intellectual property protection and industry R&D intensity jointly determine whether multinational corporations choose greenfield investment (to avoid technology spillovers) or joint ventures (to receive some spillover effects). Their analysis suggests that collaborative R&D arrangements, including joint patent applications, are not simple R&D decisions but rather entry mode choices made under institutional constraints. When intellectual property protection is moderate and R&D intensity is high, joint ventures—a form of cooperation with less equity—may be an equilibrium outcome. Naghavi and Leahy (2006) describe a specific complementarity: strong intellectual property protection makes joint ventures viable in R&D-intensive industries by balancing the risks of knowledge spillovers and the benefits of technology acquisition. Their findings suggest that the impact of any single institutional condition depends on the presence of others. This study extends this logic beyond the industry level and applies it to the national institutional configurations faced by Chinese companies in the EU. This analysis does not examine intellectual property protection or foreign direct investment review in isolation, but rather investigates how multiple institutional areas collectively influence the attractiveness of asset-light, non-equity strategies (e.g., co-inventor patents).

Co-patenting aligns conceptually with what UNCTAD (2011) classifies as a non-equity mode of international production- a contractual, low- commitment arrangement that allows firms to access foreign knowledge without taking an ownership stake. Hagedoorn (2002) provides empirical evidence that inter-firm R&D partnerships have progressively shifted from equity-based joint ventures toward contractual agreements, as the latter offer greater strategic flexibility and lower organisational costs. Narula (2001) further argues that firms choose between internal and non-internal R&D activities based on technological and institutional factors, with collaborative R&D representing a distinct non-internal, non-equity path that is reversible and involves lower capital exposure. In summary, these views support the idea that China-European co-inventor patents can be interpreted as an observable outcome of an asset-light, non-equity strategy in acquiring foreign innovation networks.

Damioli and Marin (2024) demonstrate that different entry modes (greenfield vs. cross-border M&A) have heterogeneous effects on local patent output, implying that patent statistics are sensitive to entry mode choices. Extending this logic, when institutional frictions (e.g., stricter FDI screening) raise the cost of equity-based entry, firms may substitute towards non-equity collaborative arrangements such as co-inventor patents-an observable outcome that can be captured in patent data.

Non-equity modes (NEMs) have gained prominence as alternatives to traditional FDI (UNCTAD, 2011). UNCTAD (2011) estimated that cross-border NEMs generated over $2 trillion in sales in 2010, with contract manufacturing and services outsourcing accounting for the largest share. Brouthers et al. (2022) further categorize newer forms, and identify four categories of non-traditional entry modes- capital access, innovation outposts, virtual presence, and managed ecosystems- that have gained prominence with digitalisation and global value chain integration. Collaborative patenting fits within the innovation outposts category: firms establish listening posts to access foreign knowledge without full equity commitment. This study extends this logic by using co-inventor patents as a measurable outcome of such light-asset engagement. Collaborative patenting is a measurable form of network-based knowledge integration, though it also arises from scientific collaboration and EU programmes (De Prato & Nepelski, 2012; Ervits, 2023, 2024). Thus, CPI serves as an indirect behavioural proxy for light-asset engagement rather than a direct entry-mode indicator.

De Prato and Nepelski (2012) analyse global co-invention networks using co-invention data and show that network positions strongly affect collaboration intensity. Their gravity model approach confirms that institutional proximity, including shared language and intellectual property protection, shapes co-patenting patterns. Ervits (2023, 2024) further demonstrates that university-industry collaborations produce measurable patent outcomes and that CSR reporting in Chinese enterprises reflects institutional pressures that may also influence collaborative innovation behaviour. These studies support the use of patent data as a valid indicator of cross-border knowledge integration.

Based on the above arguments, this study uses China-European co-inventor patents as a proxy of the light-asset entry mode, and views this interpretation as an explanatory perspective rather than an assertion about the inherent nature of co-patent applications. When institutional frictions increase the cost of equity entry (for example, strict FDI screening or uncertainty in intellectual property enforcement), Chinese companies may turn to more asset-light technology acquisition methods. Co-patent applications with European partners are one such method. Therefore, a higher intensity of co-patent applications does not necessarily mean higher innovation performance; it may mean that Chinese companies are maintaining their position in the European innovation ecosystem through another, less asset-intensive mode. Similarly, it may also reflect a proactive strategy of integrating into the European innovation network through the most feasible means, consistent with the strategic asset-seeking motivations emphasized in the literature (Luo & Tung, 2007; Dunning & Lundan, 2008). This study adopts this interpretation as an assumption that allows the descriptive patterns in the data to be organised within a coherent analytical framework. This does not mean that all co-patent application activities are driven by companies or are strategically motivated. It is important to clarify that the CPI is not a direct measure of entry mode, but rather an indirect behavioral indicator reflecting observable outcomes of entry mode selection. Other interpretations of cross-border co-inventor patents include inter-university research collaborations (Ervits, 2023, 2024), academic networks, and EU framework programs such as Horizon 2020 and Horizon Europe. These factors may also contribute to collaborative patent activity independently of firm-level entry strategies. This study does not aim to separate firm-level entry mode decisions; rather, it uses the CPI as a publicly observable indicator to capture the overall outcomes of various collaboration channels, including but not limited to firm-driven strategic asset seeking.

2.2 Theoretical Foundations: Configurational and Complementarity Perspectives

This study draws modestly on two core theories to guide variable selection and to help interpret the findings.

One of the theoretical pillars is Dunning's eclectic paradigm (OLI). Dunning's well-known framework breaks down overseas investment decisions into three advantages: ownership, location, and internalization (Dunning, 1993). For the purposes of this study, location advantage is paramount—it includes factors such as access to knowledge and a robust innovation ecosystem. When regulatory barriers make full internalization difficult, firms can still acquire these location advantages by choosing partner countries or regions. This point, put forward by Dunning and Lundan (2008), is central to this study's consideration of joint patent applications.

Kostova's research on institutional duality offers another valuable perspective on this issue. Her core argument is that multinational corporations experience dual pressures from both the home and host country institutions, making legitimacy in the host country a genuine challenge (Kostova, 1999). When access through equity partnerships becomes more difficult, for example, due to stricter screening rules, a shift to a lighter, less ownership-dependent mode becomes reasonable. However, the final outcome often depends on a combination of various friction factors. Success or failure hinges on a combination of conditions, with the strength of intellectual property protection and policy coordination appearing particularly crucial (Kostova, 1999; Kostova & Zaheer, 1999).

A third research path involves theoretical literature on non-equity modes, which depict the growing importance of contract-based, low-equity international production organization. UNCTAD (2011) describes non-equity modes as contractual relationships between multinational corporations and their partner companies, encompassing arrangements such as contract manufacturing, service outsourcing, franchising, licensing, and management contracts—all of which do not involve equity investment. Brouthers et al. (2022) categorize these, along with several other emerging modes, into four types: capital access, innovation outposts, virtual presence, and managed ecosystems. Co-inventor patents fall under the innovation outpost category, where firms establish offices in another country to build informal networks and seek new knowledge and resources. Following this line of thought, this study views co-inventor patents as a measurable outcome of asset-light participation.

Therefore, in our analysis, we need to consider that institutional frictions are not viewed as independent obstacles but as a whole, collectively driving Chinese companies towards a light-asset entry mode. This study does not assume a simple substitution relationship between equity financing and non-equity financing modes. Instead, it asks whether such a shift really shows up in the data, and under what combinations of institutional conditions it becomes visible. That kind of configurational thinking naturally leads to reinterpreting co-patenting as a light-asset entry mode. Papanastassiou et al. (2020) stress that R&D internationalisation today looks much more like a network, with firms relying on cross-border knowledge-sourcing strategies that do not demand a heavy equity commitment. De Prato and Nepelski (2012) arrive at a similar conclusion from a different angle: their mapping of global co-invention networks shows that collaborative patenting is a tangible, observable form of international technological collaboration, not just a statistical artefact.

When you put these ideas together, several things become clear. Dunning's OLI paradigm helps explain why knowledge-ecosystem advantages are such a strong pull for location choice (Dunning, 1993; Dunning & Lundan, 2008). Kostova's institutional duality framework clarifies how firms juggle home- and host-country pressures through adjustments in entry mode (Kostova, 1999). The NEM literature, meanwhile, documents a steady rise in contractual, low-equity arrangements for international production. Building on this OLI logic, a central premise of the OLI paradigm is that when internalisation advantages are eroded by host-country institutional constraints- such as FDI screening- firms sustain their ownership advantages through contractual or network-based control rather than equity-based control (Dunning, 1993; Dunning & Lundan, 2008). This logic provides the theoretical underpinning for interpreting co-patenting as a form of entry mode adaptation. When equity-based entry encounters heightened institutional friction, these three strands point jointly to collaborative patenting as a meaningful observable indicator. When equity-based entry hits higher frictions- strict FDI screening is a clear example- firms may shift toward lighter, more collaborative arrangements. However, the final outcome is not determined by a single factor, but rather shaped by the entire institutional structure. For example, strong intellectual property protection can buffer the negative impact of FDI screening by providing predictability at the level of legal rules required for knowledge sharing. This structural perspective provides the theoretical foundation for the exploratory analysis in subsequent chapters.

Based on the above structural logic, this study does not presuppose a direct linear relationship between any single institutional friction (e.g., the strictness of FDI screening) and the intensity of co-inventor patents. Instead, the correlation between FDI screening and co-inventor patents is expected to depend on how FDI screening is combined with other institutional conditions, particularly the alignment of intellectual property protection and industrial policy. According to Kostova's (1999) dualistic argument, sound intellectual property protection can provide legal certainty, thereby offsetting the deterrent effect of strict FDI screening and enabling asset-light collaboration. Conversely, in the case of weak intellectual property protection, strict FDI screening may exacerbate uncertainty and even inhibit non-equity collaboration (Kostova & Zaheer, 1999). This conditional, structural thinking guides the exploratory empirical analysis presented in Chapter 4.

This configurational logic draws on a broader perspective from institutional theory: institutions do not operate in isolation. Scott (2014) views institutional thickness—that is, the mutual reinforcement of regulatory frameworks—as a necessary condition for complex economic coordination. In his view, what matters is not a single strong institution (such as intellectual property protection), but whether it is situated within a coherent and complementary system of rules. Amable (2003), in his study of the diversity of capitalism, puts forward a similar view: the difference in national institutions lies not only in the level of individual arrangements but also in the degree of fit between these arrangements. Some combinations are internally consistent, while others are not.

Here, we can draw a potential conclusion. When institutions lack complementarity—for example, the coexistence of strict FDI screening and mediocre intellectual property protection—firms may find themselves in a dilemma. FDI screening hinders equity-based access, while weak legal protection makes non-equity cooperation risky. The end result is a restrictive rather than empowering combination of institutions. Therefore, the empirical analysis in Chapter 4 focuses on configurations that may inadvertently inhibit cooperation, rather than just those that encourage it.

2.3 Existing Empirical Evidence

The following empirical studies will focus on whether they support or challenge the above-mentioned configuration logic.

Some empirical articles have examined the relationship between host country innovation capacity and the technological activities of foreign firms. The results consistently show that countries with stronger innovation systems attract more knowledge-seeking firms. Countries with high R&D investment, close industry-academia-research collaboration, and strong patent output have a clear advantage, continuously attracting more technology-oriented activities from foreign investors (Autio & Thomas, 2014; Dunning & Lundan, 2008). The reason behind this is that advanced innovation ecosystems contain valuable strategic assets—tacit knowledge and skilled talent pools—which external investors have ample reason to desire.

Research on Chinese outbound investment also confirms this. Chinese companies tend to choose regions with strong technological capabilities, viewing them as a way to enhance their overall competitiveness (Luo & Tung, 2007). However, most research remains limited to foreign direct investment and mergers and acquisitions. Collaborative outcomes receive far less attention than innovation capabilities. The link between innovation capabilities and investment is now well-established. However, the role of non-equity partnerships has received little attention (Buckley et al., 2007).

This changed obviously after the EU introduced its foreign direct investment (FDI) screening mechanism in 2019. Subsequent studies have tracked a decrease in large-scale technology M&A transactions following the implementation of this framework, particularly in sensitive sectors such as semiconductors and artificial intelligence (Rhodium Group, 2020; MERICS, 2019). Simultaneously, collaborative activities appear to have increased. Chinese companies have expanded their R&D collaborations with European universities and companies, leveraging these connections to acquire knowledge while circumventing the most stringent FDI screening (Peragovics & Szunomár, 2021).

Kostova's institutional dualism perspective offers an effective way to interpret this shift. Her core argument is that when host country institutions increase regulatory pressure on investment, companies choose entry modes that require less ownership but still allow for the inflow of knowledge. The EU's FDI screening rules, which impose stricter FDI screening on foreign investment in sensitive sectors such as semiconductors, artificial intelligence, and biotechnology, serve precisely this purpose: these rules increase the compliance costs and legality risks of full acquisitions (European Commission, 2019). Correspondingly, large-scale Chinese technology acquisitions in the EU declined significantly after 2019, particularly in high-tech sectors (Rhodium Group, 2020; MERICS, 2019). However, collaborative activities did not show the same downward trend. Joint patent applications between Chinese and European inventors (especially those from Germany and the Netherlands) have increased in areas such as new energy and advanced materials, even against the backdrop of declining equity transactions (Peragovics & Szunomár, 2021). This pattern coincides with Kostova's prediction: as institutional barriers increase, companies will attempt to maintain their legitimacy and access to knowledge by shifting from asset-heavy modes to collaborative arrangements.

Institutional economics has long considered formal property rights protection as a fundamental requirement for economic exchange (North, 1990), while institutional sociology further points out that "institutional depth" (a well-developed and mutually reinforcing system of rules) determines whether knowledge-intensive cooperation can truly take root (Scott, 2014). Intellectual property-related frictions make this logic more concrete. In regions where host countries have stronger intellectual property enforcement, Chinese companies seem more willing to pursue joint patent applications, possibly because they perceive a lower risk of knowledge leakage (Kostova & Zaheer, 1999). Empirical studies of Chinese R&D institutions in Europe show a positive correlation between companies' choice of location for collaborative innovation and the host country's intellectual property enforcement and the availability of R&D subsidies (Di Minin et al., 2012).

There is less empirical research on the factor of industrial policy alignment. This refers to the overlap between the host country's strategic industries and China's outbound investment policy priorities. When both sides target similar areas—such as new energy, advanced manufacturing, and information technology—this overlap naturally creates opportunities for joint projects. This level of fit reduces the search costs for partners and conveys shared needs (Luo & Tung, 2007). From a non-equity perspective, it acts as a pull mechanism: even with limited equity access, firms can acquire knowledge through co-inventions in areas of mutual interest (UNCTAD, 2011). This suggests that industrial policy fit can synergize with intellectual property protection, making co-inventor patents an attractive asset-light strategy.

More extensive regional and cross-border patent research further confirms the importance of institutional conditions. De Prato and Nepelski (2012) demonstrate that co-inventor patents are a reliable and observable indicator of transnational R&D collaboration, particularly in technology-intensive sectors. De Noni et al. (2018) show that less developed regions in Europe can benefit from external collaboration networks, provided that the host country's institutional framework facilitates knowledge inflows. Hoekman et al. (2009) indicate that geographical and institutional proximity jointly influence the intensity of co-inventor patents across Europe. Kerr (2015) documented the rapid growth of global co-inventor patents, noting the positive role played by intellectual property protection and policy openness. Su and Moaniba (2017) confirmed that developing countries, including China, are more actively involved in international co-inventor patents when host country institutions reduce the costs of collaboration.

Two other institutional tools are also worth mentioning, although the literature provides little guidance on their connection with non-equity collaboration. R&D tax incentives reduce the after-tax cost of R&D and have been shown to increase national R&D spending (Bloom et al., 2002). State aid for innovation works through direct subsidies, procurement, and subsidized loans. Both measures demonstrate a government commitment to innovation and make a region more attractive for R&D-intensive activities. However, the impact of these incentives on the choice between equity and non-equity modes remains unclear: generous incentives can be equally effective in supporting wholly-owned R&D subsidiaries, joint ventures, or contractual collaborations. Therefore, this study uses R&D tax incentives and state aid as exploratory conditions to examine their association with CPI without presupposing any directional expectations.

Despite the abundant empirical evidence mentioned above, the research gap remains. Most empirical studies focus on a few large EU economies—Germany, France, and the Netherlands—or employ broad institutional distance indicators with very low time variability (Kaufmann et al., 2010). Systematic exploratory empirical studies covering all 27 EU member states and based on specific innovation policy indicators (such as intellectual property enforcement, R&D tax incentives, and openness to state aid) are still scarce. Furthermore, few studies use only publicly available data, employ quantitative exploratory cross-sectional designs, and include the intensity of co-inventor patents as the primary outcome variable.

2.4 Research Gap

Previous research has deepened our understanding of innovation ecosystems and institutional effects, but three shortcomings remain. First, most studies focus on foreign direct investment flows or mergers and acquisitions, paying little attention to non-equity collaboration outcomes (such as co-inventor patents) (Buckley et al., 2007; Luo & Tung, 2007). Second, most studies employ broad institutional distance indicators or focus only on a few major EU member states, rather than comparing frictions at specific policy levels across all 27 member states (Kaufmann et al., 2010; Peragovics & Szunomár, 2021). Third, existing research primarily focuses on causal or explanatory analyses, rarely conducting simple descriptive pattern analyses based solely on publicly available data.

This study addresses these shortcomings by conducting a descriptive cross-sectional analysis of the 27 EU member states. The study selects five specific institutional frictions related to innovation and explores their correlation with the intensity of China-EU co-inventor patents. The core argument is that, even without asserting causality or using corporate-level business data, the bundle of these institutional conditions can be systematically associated with the intensity of co-inventor patents.

2.5 Contribution of the Study

This thesis contributes to the existing literature in three ways. First, it proposes collaborative patenting intensity as a publicly observable indicator for measuring asset-light (non-equity) entry patterns in strategic asset-seeking activities, and does so from an explanatory perspective of organizational descriptive patterns rather than an assertion of the inherent nature of co-inventor patents. Second, it conducts a comprehensive comparative analysis of the institutions in the 27 EU member states using targeted innovation policy indicators. Third, it employs a configurational perspective to analyze institutional effects, moving beyond the additive approach commonly found in international business literature. These contributions help connect the theory of institutional duality, the eclectic(OLI) paradigm, and recent research on non-equity patterns and open innovation.

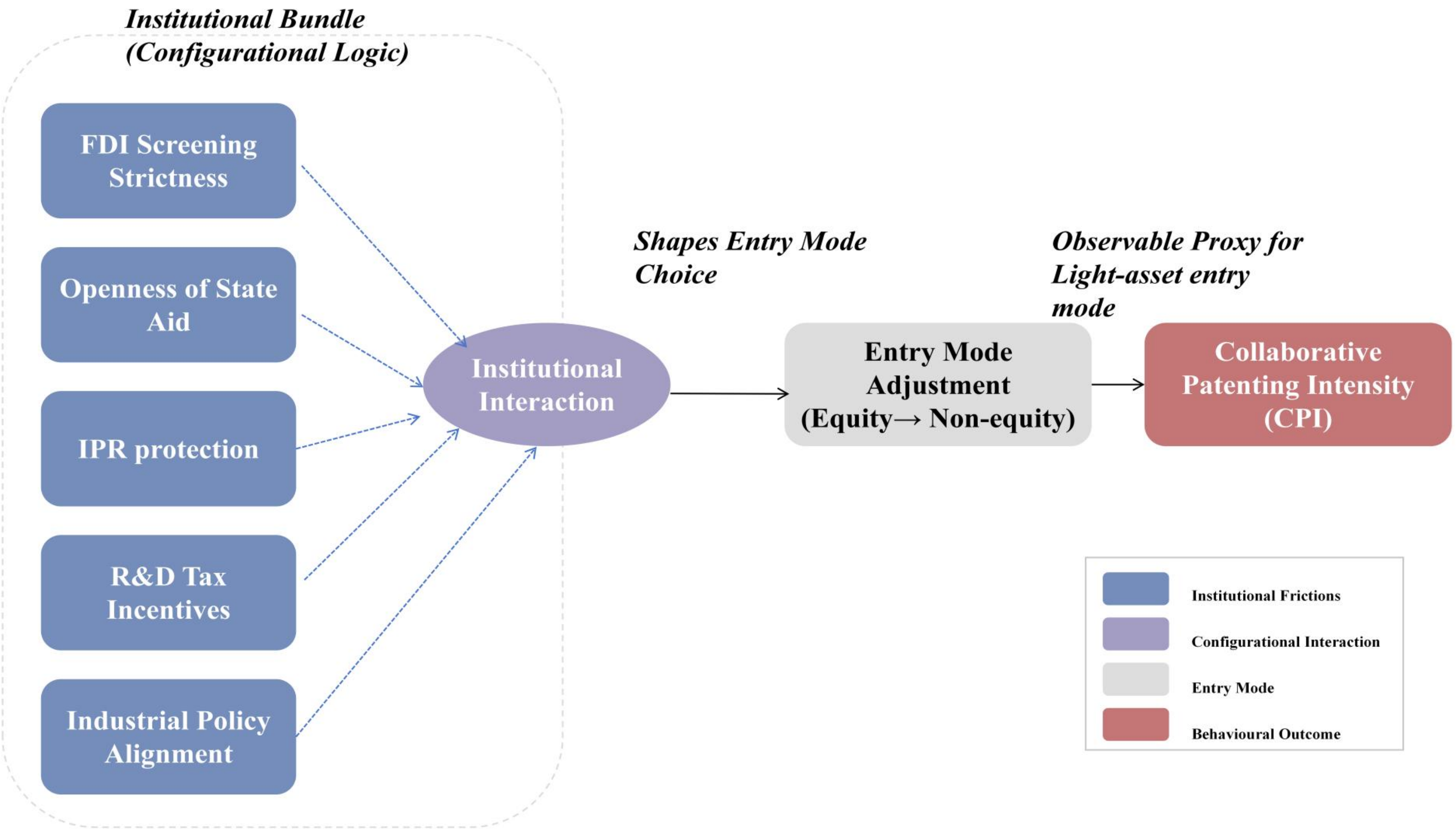

Figure 1. Conceptual Framework

Source: compiled by the author

2.6 Conceptual Framework

Figure 1 illustrates the conceptual framework of this study. This framework does not treat institutional frictions as independent drivers, but rather places them within a logic of configurational combination: the impact of any single friction on entry mode selection depends on how it is combined with other institutional pillars. A research expectation highlighted in the figure is that a combination of stringent FDI screening and weak intellectual property protection will inhibit collaborative activity. However, a sound intellectual property system can mitigate this negative impact. Coordination of industrial policies is expected to act in a similar boosting manner, enhancing incentives for co-inventor patents. This argument is not a linear main effect explanation; it anticipates that the intensity of China-EU co-inventor patents (CPI) stems from the coordination or incoordination of conditions across multiple institutional areas. By constructing the argument around institutional combinations, this framework provides a more context-sensitive explanation for innovation-driven entry mode decisions.

Data & Methodology

3.1 Research Design and Approach

The study employs an exploratory quantitative cross-sectional design to reveal the systematic link between the intensity of China-EU co-inventor patents and innovation-related institutional conditions in EU member states.

3.2 Unit of Analysis and Temporal Structure

The analytical unit of this study is the EU member states (N=27). The overall time span is from 2016 to 2022. Most institutional variables are averaged over seven years to capture stable structural characteristics. However, the Foreign Direct Investment (FDI) screening variable is an exception; its average is based on data from the 2020–2022-time window. The European Commission began publishing systematic screening reports after 2019, making data prior to 2019 unavailable. Collaborative patent data are also averaged using a similar method to smooth out short-term fluctuations. The resulting structure is a single cross-section containing 27 observations, which is more suitable for descriptive and exploratory pattern analysis.

To balance these considerations, a hybrid time strategy is necessary: firstly, stable institutional measures are required, and secondly, the structural changes brought about by the EU screening framework in 2019. Therefore, variables with high time stability—namely, intellectual property protection, R&D tax incentives, access to state aid, and industrial policy alignment—were averaged over the full period from 2016 to 2022. This reduces measurement error and reflects the institutional environment of each country as reliably as possible (Amable, 2003). Since the strictness of FDS is directly related to regulatory changes after 2019, it was averaged only over the period from 2020 to 2022. The intensity of co-inventor patents (CPI) was averaged over the full period from 2016 to 2022 to capture both pre- and post-review dynamics and maintain sufficient variability.

This study design draws on common practices in institutional and policy analysis, applicable to variables with varying degrees of time variation (e.g., Rhodium Group, 2020; Peragovics & Szunomár, 2021). Section 4.5 reports the results of robustness tests on all variables (including supplementary OLS regressions) using a uniform average window from 2020 to 2022.

It is important to note that the 2020-2022 window coincided with the COVID-19 pandemic, which disrupted international mobility, academic exchange, and R&D collaboration, and this impact was independent of foreign direct investment (FDI) screening regulations. Therefore, any temporal variations observed during this period may reflect the combined effects of health-related shocks and policy changes. The robustness tests in Section 4.5 assess the stability of patterns across different periods without attributing changes to any single factor.

3.3 Data Sources

All data were obtained from freely available public resources: Heritage Foundation Property Rights score (Heritage Foundation, 2022); OECD R&D Tax Incentives Database (OECD, 2022); EU State Aid Scoreboard (European Commission, 2022b); European Commission FDI Screening Reports (European Commission, 2022a); Industrial Policy Database (Industrial Policy Database, 2022);

OECD/Eurostat patent statistics (OECD, 2026).

Table 1

Data Sources and Variables Extracted

Data Source	Coverage	Variables Extracted
Heritage Foundation's Property Rights score	2016–2022	Patent protection strength; Enforcement efficiency
OECD R&D Tax Incentives Database	2016–2022	B-Index; effective tax subsidy rates
EU State Aid Scoreboard	2016–2022	R&D&I state aid as % of GDP; sectoral distribution
European Commission FDI Screening Reports	2020–2022	Screening mechanism coverage; averaged over 2020–2022 only for the FDS variable to capture recent policy developments
Industrial Policy Database	2016-2022	Policy intervention indicators; sectoral priorities
OECD/Eurostat Patent Statistics	2016–2022	Co-inventor patent families (China-EU)

Notes. All variables are averaged over 2016–2022 except FDI Screening Strictness (FDS), which is averaged over 2020–2022 only. Sources are publicly available as listed.

Critical Data Constraint Acknowledgment

Firm-level data, entry-mode information, and detailed bilateral investment flows are unavailable. FDI screening data are limited to post-2019. Industrial policy alignment requires simplified manual coding. These constraints are explicitly addressed in the limitations section.

3.4 Variables and Operationalization

This study will examine how combinations of institutional conditions influence collaborative patenting intensity (CPI). Hierarchical cluster analysis and cross-tabulation methods were used to identify institutional bundles and explore their relationships with the outcome variable (see Section 3.5 for details).

The dependent variable-Collaborative patenting intensity serves as a publicly observable proxy for the intensity of cross-border knowledge integration between China and EU member states. Following OECD definitions, collaborative patenting is measured through co-inventions, i.e., patent applications in which inventors from

China and an EU country collaborate in the inventive process (OECD, 2026).

Specifically, CPI is calculated as follows:

For each EU member state, the total number of patent applications (EPO, USPTO, and PCT) with at least one Chinese inventor and at least one inventor from that EU country is summed. Only records with cooperation type “CO” (patents with foreign co-inventor(s)) are included.

To avoid double-counting in multi-inventor patents, fractional counting is applied where appropriate.

The resulting count is averaged over the period 2016–2022 and normalised by the EU country’s average population (in millions) to ensure comparability across countries of different sizes.

The formal expression is:

$$CPI_j = \frac{\sum_{t=2016}^{2022} \text{China-EU co-inventor patents}_{j,t} / 7}{\text{Population}_j(\text{millions, average 2016-2022})}$$

Where j denotes the EU member state. All data used in this study come from the OECD STI Patents Indicators database, which builds on patent records from the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the Patent Cooperation Treaty (PCT) to measure international cooperation. Higher collaborative patenting intensity (CPI) indicates more visible patterns of joint knowledge creation between Chinese and EU inventors.

This indicator was chosen for two practical reasons. First, it directly reflects the state of cross-border innovation cooperation, which aligns well with the themes of innovation management and international technology cooperation focused on in this study. Second, it does not require data on firm-level entry patterns or investment flows, data that is often unavailable to external researchers.

Following terminology from configurational analysis (Ragin, 2008), these five institutional variables are referred to as "condition variables." This term emphasizes that their effects are combinatorial—no single variable can function alone.

Take Intellectual Property Rights (IPR) as an example. This variable is measured using a property rights score (0-100), derived from the rule of law pillar of the

Heritage Foundation's Index of Economic Freedom. This indicator aims to reflect a country's strength of protection for tangible property and intellectual property rights. In practice, this means it reflects factors such as the strength of patent protection, the effectiveness of intellectual property law enforcement, and the credibility of the overall intellectual property legal framework. Higher scores indicate stronger protection and, in the context of this study, lower institutional friction in this area. Data are averages from 2016 to 2022.

$$IPR_j = \frac{1}{n} \sum_{t=2016}^{2022} PropertyRights_{j,t} \quad (n \leq 7)$$

R&D tax incentives are measured by the implied marginal tax subsidy rate, calculated as 1 minus the B index. A higher value indicates more generous R&D tax incentives (a greater marginal incentive for companies to invest more in R&D), and correspondingly lower institutional frictions.

$$RDT_j = \frac{1}{n} \sum_{t=2016}^{2022} (1 - BIndex_{j,t}) \quad (n \leq 7)$$

BIndex$_{j,t}$ represents the implied tax rate (OBS_VALUE) for the corresponding year.

State Aid Accessibility (SA): The percentage of GDP for R&D and innovation-related state aid, data from the EU State Aid Scoreboard (average from 2016-2022).

$$SA_{j,t} = \frac{\sum Aidelement_{j,t}(RDI)}{GDP_{j,t}} \times 100$$

$$SA_j = \frac{1}{n} \sum_{t=2016}^{2022} SA_{j,t} \quad (n \leq 7)$$

FDI Screening Strictness (FDS): Based on the European Commission's FDS report, the average strictness score of national FDS screening mechanisms during 2020-2022 (0=none, 1=partial, 2=full, some countries reach 3, indicating a very strict system). This continuity indicator reflects the intensity and gradual expansion of investment screening in EU member states. A shorter time window was chosen to reflect the regulatory reality after 2019, rather than the situation before the framework was established. All other institutional variables use a longer time window of 2016-2022 because these variables have higher time stability.

Industrial Policy Alignment (IPA): The degree of industry overlap between the host country's industrial policy priorities and China's strategic industries (such as advanced manufacturing, digital technology, and new energy in the core areas of "Made in China 2025").

Operationalized as the number of overlapping strategic sectors (IPA, ranging from 7 to 12) and the share of strategic sectors in the host country's policy portfolio (IPA_overlap_share, %). Both indicators are constructed through manual coding based on the Industrial Policy Database (Excel) and documented in the appendix. Higher values indicate greater alignment and potentially lower institutional friction for China-EU knowledge integration activities.

All institutional variables are averaged over the available years within 2016–2022 to account for their limited temporal variation. Control variables include GDP per capita and total R&D expenditure (% of GDP) from Eurostat. Section 3.5 details how these variables are analyzed in combination

3.5 Analytical Strategy

The analysis proceeds in five fully executable stages using standard statistical software (Python).

Stage 1: Descriptive Institutional Profiling

Hierarchical cluster analysis using Ward's method is applied to the standardised scores of the five condition variables (IPR, RDT, SA, FDS, and IPA). A four-cluster solution was selected over a three-cluster solution because the fusion coefficient plot (elbow method) showed a marked jump (substantial increase in within-cluster heterogeneity) after the fourth cluster, and the resulting groups offered clearer theoretical separation (Nordic/Western core vs. Continental/mixed vs. Eastern transition vs. Peripheral). This choice also provides more balanced group sizes and better interpretability consistent with configurational institutional analysis (Amable, 2003; Schiehll et al., 2014, Witt & Jackson, 2016). Results are visualised through a dendrogram and a heatmap of institutional scores by cluster.

For descriptive interpretation of cluster profiles (Section 4.1) and configurational cross-tabulations (Section 4.3), this study classifies country-level scores on each institutional variable into three ordinal categories: low, moderate, and high. The classification is based entirely on the empirical distribution of the 27 EU member states for each variable, using the 33rd and 67th percentiles as cutoffs. Specifically, for a given variable, a score below the 33rd percentile is labelled 'low', between the 33rd and 67th percentiles (inclusive) is 'moderate', and above the 67th percentile is 'high'. These percentiles are calculated separately for each variable using the averaged values over 2016–2022 (except FDS, which uses 2020–2022). The exact percentile values are reported in the notes to Table 2 and in Appendix Table A1.

Stage 2: Bivariate Pattern Analysis

Analysis of variance (ANOVA) is used to compare mean CPI values across the identified institutional clusters.

Pearson correlation coefficients and scatterplots with LOESS smoothing are generated to examine bivariate relationships between each condition variable and CPI. LOESS (locally estimated scatterplot smoothing) is applied to explore potential non-linear relationships without imposing a functional form, using a span of 0.75 to balance smoothness and local sensitivity.

Stage 3: Configurational Pattern Exploration

Bivariate analysis identifies the direction of association between individual institutional conditions and CPI, but it cannot reveal the combined effects of conditions. Based on the configuration logic proposed in Chapter 2, this stage further explores the non-additive interactions of institutional conditions through cross-tabulations.

The configurational cross-tabulations explore how combinations of institutional conditions associate with CPI. High and low levels are defined by the sample median. This median-split approach is transparent and robust to outliers in small samples. Conditional means of CPI are reported for each configuration. These tables are interpreted as exploratory pattern identification, not formal statistical tests.

Unlike the descriptive classification used in the cluster analysis (aimed at characterizing institutional features from three ordered levels), the third-stage configuration cross-tabulation analysis employed a simpler dichotomy (high/low) based on the sample median. This is a widely used method in configuration analysis and fuzzy set qualitative comparative analysis (fsQCA) studies (Witt & Jackson, 2016; Schiehll et al., 2014), aiming to clearly identify the combined effects of institutional conditions. To further explore the relationship between institutional configuration and the intensity of co-inventor patents, this study further divided the dependent variable (CPI) into three levels: low, medium, and high, and examined the probability of a country falling into the high-intensity group under different configurations. Dividing the condition variables by the median and the outcome variable into three levels helps maintain statistical power in small samples, and this approach reveals richer pattern information than analysis using only continuous variables.

Stage 4: Supplementary Linear Benchmark

As a supplementary linear benchmark, we conducted a series of exploratory OLS regressions to test whether the bivariate association still holds after controlling for economic growth. Given the small sample size (N=27), including all institutional variables in a single regression model would severely reduce degrees of freedom, leading to unstable estimation results. Therefore, a multi-model approach was used in the supplementary regression analysis. Each model included a maximum of three institutional condition variables and two control variables (GDP per capita and GERD), thus preserving sufficient degrees of freedom (22–24). Model 1 focused on two conditions of greater theoretical concern (IPR and IPA). Model 2 replaced IPA with FDS to assess the screening effect separately. Model 3 included only RDT and SA as alternative policy tools. Model 4 simultaneously examined all three condition variables showing the strongest configuration pattern (IPR, IPA, and FDS). These models were not used for causal inference or model selection; they served as descriptive linear benchmarks for comparison with configuration analysis results (cluster analysis and crosstabs). Due to the small sample size and the exploratory nature of this study, the results should be interpreted with caution.

The simplified model (see Table 6) was chosen based on the theoretically more reasonable model and the one with the lowest AIC/BIC value (full comparison in Appendix Table A6). All other models are listed as robustness tests in Appendix A7. All continuous variables were scaled in their original form.

The resulting coefficients were interpreted as partial correlations, not causal effects. We examined the variance inflation factor (VIF) to detect redundant variables; notably, the human resources in science and technology (HRST) variable was removed from the preferred model due to its high collinearity caused by a VIF exceeding 10, which would lead to unstable coefficients. In this paper, regression results are treated as descriptive patterns, not causal relationships. A complete comparison of the models is documented in Appendix A.

Stage 5: Sensitivity and Robustness

To assess the stability of the observed patterns, we conducted several robustness tests. First, we excluded Luxembourg, Malta, and Cyprus to examine whether small economies influenced the results; second, we removed Finland and Sweden in further tests due to their high CPI values. We repeated the cluster analysis without the FDI screening variable and applied a ternary calibration method based on ternary values to the configurational analysis. Furthermore, we applied bootstrap resampling (1000 iterations) to the two main bivariate correlations (IPR-CPI and IPA-CPI) to construct 95% confidence intervals, thus providing a nonparametric test for sampling variability with a small sample size. These steps collectively assessed whether the core patterns were excessively influenced by country-specific or coding-specific decisions.

3.6 Reproducibility of Results, and Declaration of AI Use

All analyses were performed using Python 3.10 (pandas, scipy, scikit-learn, statsmodels). Code and data extraction scripts are available upon request to ensure the reproducibility of the research results.

During the writing of this paper, the authors used ChatGPT-4 (OpenAI, 2026) for language polishing, grammar checking, and format validation. Python code for data processing, statistical analysis (cluster analysis, regression analysis, robustness tests), and visualization (heatmaps, dendrograms, scatter plots) was debugged and optimized with the assistance of Claude (Anthropic, 2026). All AI-generated outputs have been reviewed, edited, and validated by the authors, who bear full responsibility for the final content.

Results and Discussion

This chapter presents the findings from the descriptive analysis of institutional configurations and collaborative patenting intensity across 27 EU member states. Drawing on the methodological framework outlined in Chapter 3, the analysis proceeds in five stages: identifying institutional clusters, examining bivariate associations, exploring configurational patterns, and testing supplementary multivariate relationships. All institutional variables except FDI screening cover the period 2016–2022; FDS data are limited to 2020–2022 to align with the implementation of the EU screening framework.

4.1 Institutional Configuration Profiles

Hierarchical cluster analysis using Ward's method identifies four distinct institutional profiles among EU member states. Table 2 presents the mean values of institutional and control variables across these clusters.

Table 2

Mean Values of Institutional and Control Variables across Four Institutional Clusters

Cluster	Member States (n)	IPR	RDT	SA	IPA	FDS	CPI
1. Peripheral mixed	PRT, BGR, CYP, CZE, MLT, EST, LUX, GRC, HRV, SVN (10)	72.7	0.108	1.92	7.80	0.57	0.85
2. Eastern transition	HUN, POL, LVA (3)	65.34	0.167	6.76	11.00	2.33	0.58
3. Nordic/Western core	NLD, AUT, FIN, DNK, BEL, IRL, SWE (7)	88.72	0.121	1.19	10.57	1.10	19.79
4. Continental/mixed	ITA, LTU, FRA, ESP, DEU, ROU, SVK (7)	74.94	0.235	1.53	11.29	2.43	2.92

Notes. IPR = Intellectual Property Rights; RDT = R&D Tax Incentives (1 minus B-Index); SA = State Aid (% of GDP); IPA = Industrial Policy Alignment (count of overlapping sectors, range 7–12); FDS = FDI Screening Strictness (0–3 scale); CPI = Collaborative Patenting Intensity.

Classification thresholds (33rd / 67th percentiles across 27 EU countries):

IPR = 68.5 / 79.2; RDT = 0.115 / 0.198; SA = 1.32 / 3.21; IPA = 8.7 / 10.4; FDS = 0.85 / 2.05.

'Low' = score < 33rd percentile; 'Moderate' = 33rd ≤ score ≤ 67th; 'High' = score >

67th.
All cluster-level classifications in this table follow this same empirical distribution-based rule.

The Nordic-Western core (Cluster 3) stands out with the strongest innovation-relevant profile in the sample. It combines very high intellectual property protection (averaging 88.72) with only moderate FDI screening (FDS = 1.1) and favourable industrial policy alignment. These conditions closely match Amable's (2003) argument that certain coordinated economies do not merely benefit from being "coordinated" in a general sense; rather, they owe their superior performance to the way specific institutions complement one another. The cluster's exceptionally high mean collaborative patenting intensity of 19.79 is consistent with that logic.

A rather different picture emerges in the Continental/mixed cluster (Cluster 4), which includes several large economies such as Germany, France, Italy, and Spain. This group exhibits relatively stringent FDI screening, moderate levels of intellectual property protection, and varying degrees of industrial policy alignment. Notably, despite increased FDI screening, there has been no surge in asset-light cooperation; the average CPI remains at a moderate level of 2.92. This contrasts sharply with the Nordic-Western core economies and is notable. This suggests that stringent FDI screening itself does not automatically encourage non-equity cooperation among firms. What truly matters is the strength of the surrounding institutional environment, particularly the level of intellectual property protection. In other words, the effectiveness of FDI screening depends on complementary institutions. Studies by Schiehll et al. (2014), Amable (2003), and Witt and Jackson (2016) reinforce this view.

The Eastern transition economies (Cluster 2) also exhibit similar conditional dynamics, but from a different perspective. Here, high levels of state aid (6.76) and stringent FDI screening (2.33) coexist with significantly weak intellectual property protection (65.3), resulting in an extremely low average CPI of only 0.58. The institutional duality theory offers a plausible explanation: when formal protection mechanisms are weak, firms may avoid joint patent arrangements regardless of industry prioritization (Kostova & Zaheer, 1999).

Finally, Cluster 1, the peripheral mixed group, (covering a wide range from Luxembourg to Bulgaria) has a moderate level of institutional development and very light FDI screening (0.57). Their average CPI of 0.85 further suggests that, in the absence of strong intellectual property protection, an open investment environment alone is insufficient to attract co-inventor patents. In summary, these patterns highlight the configurability of institutional effects: the outcome of any particular friction depends to a large extent on the accompanying institutional conditions.

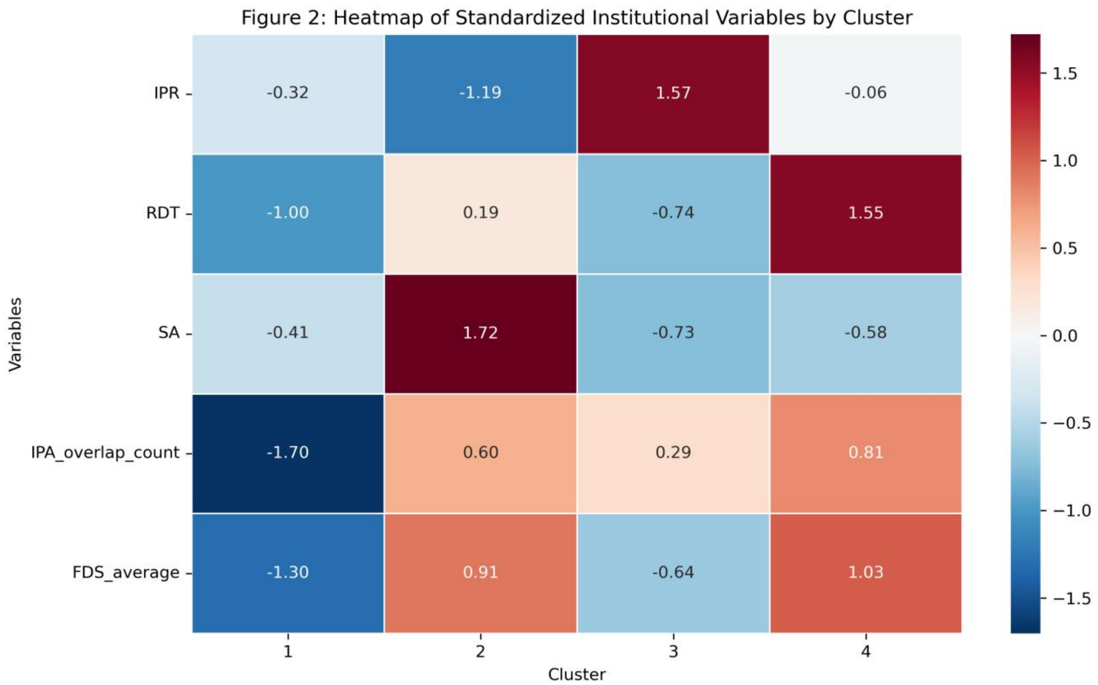

Figure 2. Heatmap of Standardized Institutional Variables across the Four Clusters (Ward's Method)

Note. Variables standardized to z-scores. Darker shades indicate higher values. Data: 2016–2022 (FDS: 2020–2022).

The heatmap in Figure 2 shows that the Nordic-Western core region (Cluster 3) not only scores higher in intellectual property protection but also maintains this advantage across all measures of friction. In contrast, the Eastern transition economies (Cluster 2) exhibit an unbalanced pattern—generous state aid and strict FDI screening coexist with the lowest intellectual property scores in the sample. The marginal mixed group (Cluster 1) shows neither a leading edge nor any obvious weakness across any dimension, exhibiting a stable, moderate profile corresponding to its modest cooperative output. Most notably, the continental/mixed cluster (Cluster 4): Germany and France combine moderate intellectual property protection, high screening mechanisms, and strong policy consistency, a configuration that appears as a patchwork of mid-to-high values in the heatmap, unlike the coherent dark bars of Cluster 3. This visual irregularity suggests why, despite their large market size, their CPI remains low—their institutional mix lacks the internal consistency characteristic of the best-performing group.

The tree diagram (Figure 3) illustrates the hierarchical structure of these groups. As described in Section 3.5, we retained the four-cluster scheme; Table 2 lists the final classification results.

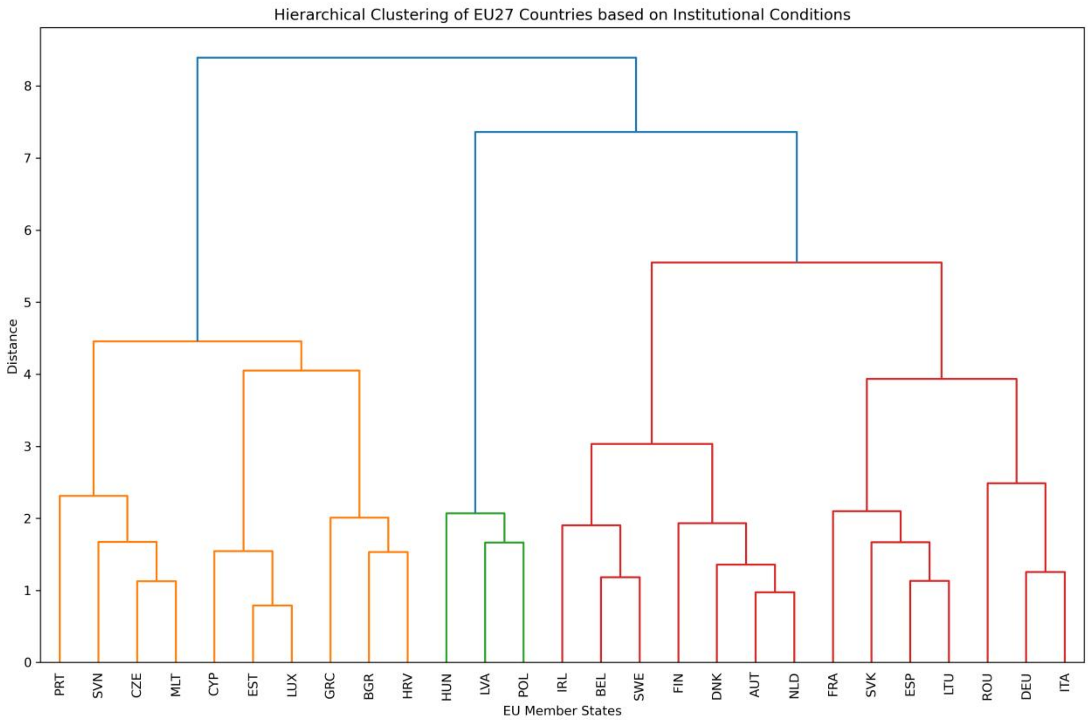

Figure 3. Dendrogram of Hierarchical Cluster Analysis of EU Member States' Institutional Profiles

4.2 Bivariate Associations with Collaborative Patenting

Table 3 presents Pearson correlation coefficients between the institutional variables, control variables, and collaborative patenting intensity (CPI). IPR protection shows the strongest positive association with CPI, followed by industrial policy alignment. R&D tax incentives and state aid show negative associations, although these are weaker. FDI screening exhibits a very weak negative association. Notably, the economic development indicators (GDP per capita and GERD) show almost no association with CPI.

This pattern suggests that regulatory and policy conditions matter more than general economic scale for collaborative patenting activity. Cluster-wise mean comparison indicates marked dispersion in CPI across the four profiles. These bivariate patterns provide initial support for the importance of specific institutional conditions and are explored further through configurational analysis in Section 4.3.

Table 3

Pearson Correlations between Institutional Conditions, Control Variables, and Collaborative Patenting Intensity (CPI)

Variable	**Correlation**
IPR	0.581
IPA	0.371
RDT	-0.287
SA	-0.235
FDS	-0.032
GDP per capita	-0.004
GERD	0.167
HRST	0.04

The four clusters showed significant inter-group differences in CPI (ANOVA: $F(3, 23) = 8.67$, $p < 0.001$), with the mean of the Nordic/Western core cluster (19.79) being much higher than that of the other groups.

Figure 4 plots each institutional variable against collaborative patenting intensity, overlaying a LOESS-smoothed curve that captures local trends without imposing a rigid functional form. The scatter for IPR protection slopes unmistakably upward: countries with Heritage Foundation scores above 80 tend to cluster in the upper reaches of the CPI distribution, while the low-IPR cases crowd the origin. Industrial policy alignment tells a similar story, though the cloud is looser, reflecting how sectoral overlap opens doors but does not guarantee that firms walk through them. The R&D tax incentive panel looks almost flat, with the LOESS line hovering near zero slope- a visual confirmation that marginal subsidy generosity, at least in this cross-section, carries little explanatory weight. State aid and FDI screening scatter even more diffusely, and their smoothed trajectories waver, suggesting that these instruments do not shape co-patenting in any straightforward linear fashion. In conclusion, these five groups oppose simply viewing institutional quality as "the more the better"; only the systematic gradation of intellectual property protection and policy coordination is sufficient to justify considering them as the main levers.

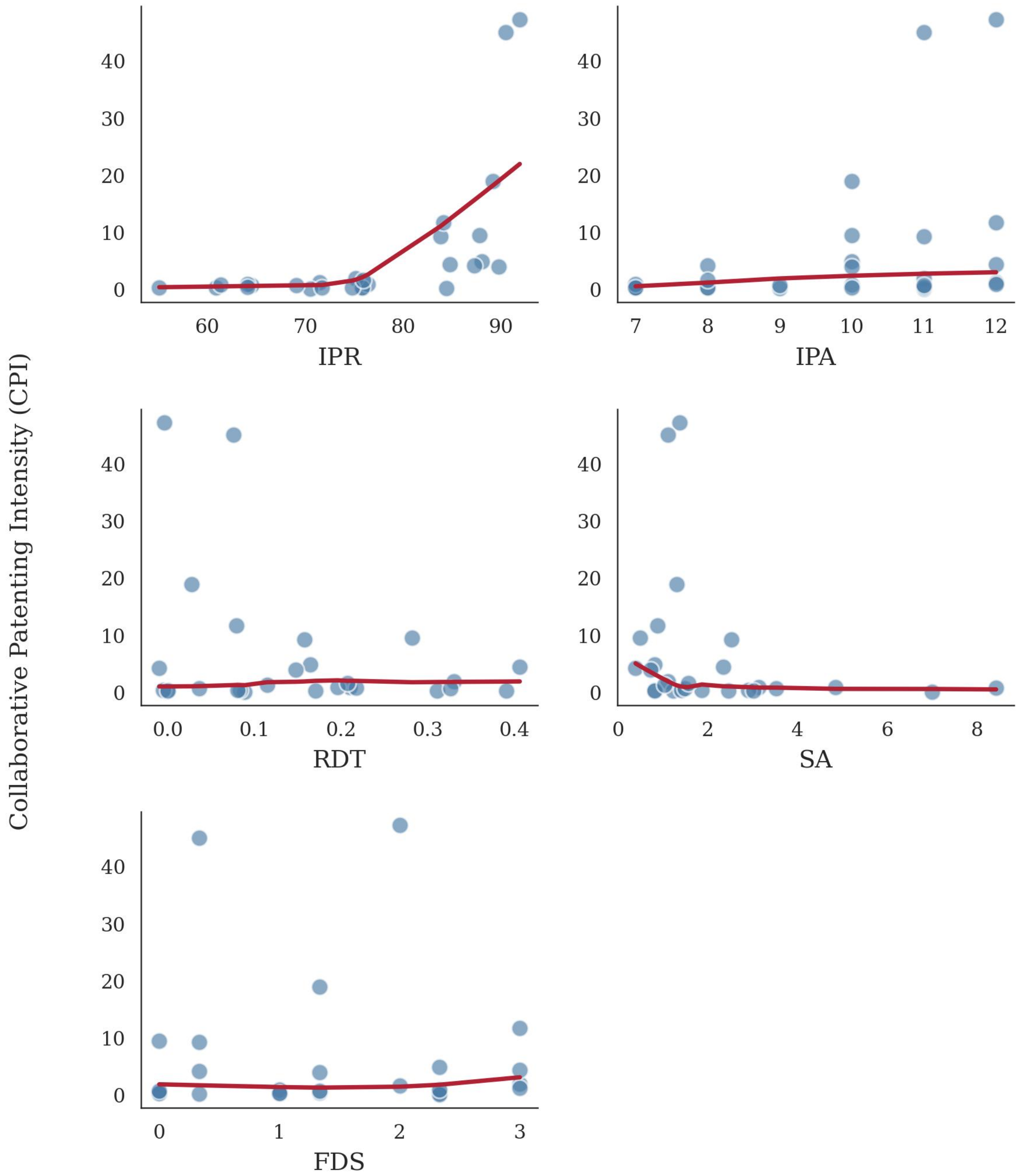

Figure 4. Bivariate scatterplots of CPI against institutional variables with LOESS smoothing

4.3 Configurational Patterns

While bivariate analysis can identify the direction of the association between individual institutional conditions and collaborative patenting intensity (CPI), it fails to capture the joint, non-additive effects emphasized by the configuration perspective. Therefore, this phase will explore how combinations of institutional conditions are related to CPI through conditional means and distribution patterns.

This study uses a median dichotomy (high/low) for institutional conditions and a ternary grouping method (low/medium/high) for CPI. These two threshold definitions serve different purposes: one helps to clearly demonstrate institutional combinations; the other allows for a more detailed observation of the distribution of outcome variables. In fact, regardless of the method used, the direction of the results remains unchanged (this is explained in more detail in the robustness test section).

Table 4 lists the conditional mean CPI for the combination of intellectual property protection (IPR) and industrial policy alignment (IPA). The results show a significant complementary effect. Countries with high levels of IPR and high industrial policy alignment have the highest average CPI (23.49), more than four times that of countries with high levels of IPR but low industrial policy alignment (5.50). In contrast, countries with low levels of intellectual property protection have lower CPIs regardless of the degree of alignment with their industrial policies. These results strongly supports the previously mentioned theoretical expectation that sound intellectual property protection can provide the legal certainty needed for knowledge sharing, while alignment with China's strategic industries can provide concrete opportunities for cooperation (Dunning & Lundan, 2008).

Table 4
Conditional Mean Collaborative Patenting Intensity by High/Low IPR and High/Low Industrial Policy Alignment

Configuration	**IPA Low**	**IPA High**	**n (Low/High)**
High IPR	5.5	23.49	8/5
Low IPR	0.4	0.85	8/6

To further examine whether specific configurations systematically increase the likelihood of high CPI outcomes, an additional analysis was conducted using CPI tertiles (Low/Medium/High). Table 5 reports the frequency distribution across these tertiles.

Table 5
Configurations of IPR Protection and Industrial Policy Alignment by CPI Tertiles

Configuration	Low CPI	Medium CPI	High CPI	% in High CPI
Low IPR + Low IPA	6	2	0	0.00%
Low IPR + High IPA	2	4	0	0.00%
High IPR + Low IPA	1	3	4	50.00%
High IPR + High IPA	0	0	5	100.00%

As shown in Table 5, this complementary logic is more evident from a distributional perspective. All five countries with high levels of intellectual property protection and high industrial policy alignment entered the high CPI tertiary (100%), while countries with low levels of intellectual property protection, regardless of their industrial policy alignment, did not enter the high CPI group. This indicates that stronger intellectual property protection and policy coordination not only increase the average CPI but also consistently produce higher performance outcomes.

We also examined other two-way configurations to explore other potential interactions. The combination of intellectual property protection and the stringency of foreign direct investment (FDI) screening (see Appendix Table A3) shows that when intellectual property protection is strong, strict screening has a limited negative impact on performance. Similarly, the interaction between state aid and FDI screening (see Appendix Table A4) suggests that a crowding-out effect may exist in environments with high levels of government intervention. While these patterns are valuable, their importance is less than the main complementarity already found between intellectual property and industrial policy alignment.

To explore more complex interactions, we conducted a three-way configuration analysis. We examined the combined effects of IPR, IPA, and FDI screening strictness (FDS) on mean CPI (see Appendix Table A5 for full version). The highest value (27.09) occurs in the configuration combining High IPR, High IPA, and Low FDS — exemplified by Finland and Sweden. When High FDS is added to the High IPR + High IPA combination, mean CPI declines moderately to 21.08. This indicates that while strict FDI screening may weaken collaboration to some extent, its negative impact is largely buffered by strong IPR protection and policy coordination.

Conversely, all configurations involving Low IPR protection exhibit CPI values below 1.0, regardless of the levels of IPA and FDS. This highlights that weak IPR appears to pose a binding constraint on China-EU co-inventor patents.

In conclusion, the configuration analysis demonstrates that the impact of institutional factors on co-inventor patents is inherently combinatorial, rather than simply additive. The most favorable environment comes from strong intellectual property protection and industrial policies that are highly aligned with China's strategic sectors, while foreign direct investment review plays a secondary and conditional role.

4.4 Supplementary Regression Analysis

Configuration analysis reveals the combination logic of institutional conditions, but it cannot answer a follow-up question: when IPR and IPA are forced to be treated as linear variables, do their partial correlation directions remain consistent? Table 6 provides this linear baseline, the main purpose of which is not to confirm the effect size, but to examine whether configuration findings are sensitive to model specification.

As outlined in Section 3.5, this supplementary analysis adopts a parsimonious approach. The preferred OLS specification includes the two institutional variables that showed the strongest and most consistent associations in the preceding analyses—IPR protection and industrial policy alignment—together with two economic controls (GDP per capita and GERD). This model was selected from a set of theoretically plausible alternatives based on the lowest AIC/BIC (see Appendix Table A6). All continuous variables enter in their original scales. Table 6 reports unstandardized coefficients for substantive interpretation.

The results indicate that IPR protection and industrial policy alignment (IPA) are positively associated with collaborative patenting intensity, with IPR remaining statistically significant ($p < 0.05$) and IPA marginally significant ($p < 0.10$). In contrast, GDP per capita and GERD show no meaningful partial associations once

IPR and IPA are controlled for. This pattern is consistent with the correlation matrix and suggests that, in this small sample, aggregate economic size and overall R&D intensity contribute limited additional explanatory power beyond the core institutional factors.

In addition, supplementary OLS regressions using only the 2020–2022 window (Table A8 in Appendix A) yield highly consistent results with the main specification. IPR protection remains positive across models, while industrial policy alignment (IPA) continues to show a positive association (significant in the fuller specification). These findings confirm that the core relationships are robust to the choice of temporal window, even when focusing on the post-FDI screening framework period that overlaps with the COVID-19 pandemic.

Diagnostic checks confirm that the model is suitable for descriptive purposes. Variance inflation factors (VIFs) for all predictors are low (all < 1.4; see Appendix Table A9), indicating no problematic multicollinearity despite the relatively high condition number caused by scale differences. The Human Resources and Technology (HRST) variable was excluded from the preferred specification because its VIF exceeded 10, which would render its coefficient unstable (see Section 3.5 for details).The VIF values of the remaining variables were all between 1.06 and 1.38, well below the commonly used warning threshold of 5, indicating that the model did not have serious multicollinearity problems. Due to the small sample size (N=27), these regressions serve only as supplementary descriptive evidence and should not be interpreted as confirmatory causal tests. All regression results are best viewed as part of the broader pattern identification exercise.

Table 6
Main Parsimonious OLS Regression Results (Model 1)

Variables	**Unstd. Coefficient**	**Robust SE**	**z**	**p-value**
IPR	0.668	0.269	2.48	0.013
IPA	2.136	1.268	1.68	0.092
GDP_per_capita	0.000013	0.000039	0.34	0.736
GERD	-0.000082	0.000109	–0.75	0.456
Constant	-65.278	28.841	–2.26	0.024

Notes: Model Statistics: $R^2 = 0.421$, Adjusted $R^2 = 0.316$, N = 27

All p-values are reported for descriptive pattern comparison only and should not be interpreted as evidence of statistical significance or causal effects given the small sample (N=27) and exploratory nature of the analysis.

4.5 Robustness Checks

Several sensitivity analyses were conducted to assess the stability of the configurational patterns and the supplementary regression findings.

First, we examined the robustness of sample composition. Excluding small countries (Luxembourg, Malta, and Cyprus) reduced the sample to N=24, but the core correlation patterns remained intact (IPR-CPI r = 0.599; IPA-CPI r = 0.350). Similarly, excluding Finland and Sweden—two countries with exceptionally high CPI values—did not materially alter the main patterns.

Second, to address the hybrid temporal structure of the variables, all variables including the dependent variable (CPI) were restricted to the 2020–2022 period using yearly co-patent and population data. The bivariate correlations remained similar to the main analysis (IPR r = 0.576 vs 0.581; IPA r = 0.359 vs 0.371). Supplementary OLS regressions using the 2020–2022 CPI produced qualitatively consistent results, with some modest changes in coefficient magnitudes (see Table A7,A8 in Appendix A).

Third, re-running the cluster analysis without the FDI screening variable yielded a somewhat different four-group structure, yet substantial differences in CPI across groups persisted. This suggests that IPR protection and industrial policy alignment, rather than FDI screening alone, are the primary drivers of institutional differentiation. Table 7 summarizes the key robustness checks.

Table 7

Results of Robustness Checks

Robustness Test	Key Finding	Implication
Temporal window (2020–2022 only)	IPR r = 0.576 (main: 0.581) IPA r = 0.359 (main: 0.371) Regression coefficients qualitatively consistent	Main patterns are robust to temporal specification
No FDS variable	4-cluster solution remains broadly stable	FDS has limited influence on overall grouping
Exclude small countries (N=24)	Core correlations remain consistent	Robust to sample composition
Exclude FIN & SWE (N=25)	Patterns largely unchanged	Not primarily driven by high-CPI Nordic countries

Notes. Detailed regression outputs for both periods are reported in Appendix A (Tables A7 and A8). All robustness checks support the overall stability of the configurational patterns.

As planned in the sensitivity analysis (Section 3.5), bootstrap resampling (1,000 iterations) generated 95% confidence intervals for the IPR-CPI correlation [0.48, 0.73] and IPA-CPI correlation [0.16, 0.58]; neither interval includes zero.

4.6 Discussion

The patterns observed in the cluster analysis and cross-tabulations align with the configurational perspective developed in Chapter 2. The cluster analysis and cross-tabulation results show that institutional conditions do not influence Chinese firms' light-asset entry mode (collaborative patenting) in a simple additive manner. Instead, specific combinations of strong IPR protection and high industrial policy alignment are associated with substantially higher collaborative patenting intensity.

The supplementary regression analysis yields consistent patterns, with IPR and IPA showing positive associations. However, given the small sample size (N=27), these regression results should be interpreted with caution and are presented only as supplementary evidence. The configurational approach adopted in this study is more suitable for revealing complex interdependencies among institutional variables than traditional linear regression models.

The robustness checks, including the temporal window sensitivity analysis and alternative model specifications, further strengthen confidence in the main findings. These results suggest that Chinese firms strategically use collaborative patenting as a flexible, non-equity entry mode when host-country institutional bundles are supportive of technological collaboration, even in the presence of stricter FDI screening.

As shown in Section 4.1, the Nordic-Western core (Cluster 3) combines strong IPR with moderate screening and yields the highest CPI. Theoretically, this aligns with the notion of institutional thickness discussed in Section 2.2 (Scott, 2014)- dense regulatory frameworks that protect intellectual property while facilitating knowledge flows. In contrast, the large but heavily regulated markets of Cluster 4, despite their economic weight, generate institutional frictions that suppress the specific form of collaboration measured by CPI.

At first glance, there appears to be a tension between Kostova's (1999) institutional duality logic and the low collaborative patenting intensity found in Cluster 4—countries like Germany and France. Kostova's framework would lead us to expect that stricter FDI screening pushes firms toward lighter, non-equity modes of entry. But the numbers do not show a straightforward shift toward more co-patenting in these economies. In Cluster 4, strict FDI screening coincides with only moderate IPR protection. This combination appears to create a "double friction" environment: equity modes are restricted, while asset-light collaborations face insufficient legal certainty, resulting in observed lower CPI. This pattern suggests that the substitution mechanism proposed by Kostova (1999) presupposes strong intellectual property protection.

More importantly, the substitution mechanism is not automatic. For a mechanism to be effective, it must be both feasible and attractive. In the case of co-inventor patents, its feasibility largely depends on the strength of intellectual property protection. In Cluster 4, strict screening (FDS =2.43) sits alongside only moderate IPR protection (mean 74.9, classified as moderate by the 33rd/67th percentile cut-offs). This results in the double dilemma anticipated in the theoretical framework (Section 2.2): equity acquisitions are hindered or costly due to screening, while joint patent applications are inhibited because the legal environment does not provide sufficient certainty to ensure the protection of shared knowledge. Firms caught in this dilemma may scale back their technology-seeking activities in these countries or turn to less formal collaborations—those that leave no trace in the patent record.

The Nordic-Western core (Cluster 3) provides the contrasting case. Here, screening is strict-to-moderate (FDS = 1.1), but IPR protection is very high (88.7). The deterrent effect of screening is substantially offset by strong legal safeguards, which makes co-patenting a viable path. That goes a long way toward explaining the high mean CPI of 19.79 in Cluster 3. So the empirical pattern does not contradict Kostova's argument; it adds an important condition. Substitution toward light-asset entry modes is conditional on complementary institutional conditions, and among these, the strength of IPR protection seems to matter most.

4.7 Limitations

While the intensity of co-inventor patents is a useful and publicly available indicator of cross-border knowledge integration, it also has some limitations. First, it only reflects successful patent applications, potentially underestimating informal knowledge exchanges or collaborations that did not lead to patent applications. Second, the absolute number of China-EU collaborative inventor patents is relatively low for many small EU countries, which may result in a large number of zero or near-zero observations, thus reducing the variability of the dataset. Third, the patent data reflects the outcome of collaboration, not the decision-making process at the firm or individual level. Finally, differences in patent application tendencies and information disclosure practices among countries may introduce some measurement errors. In interpreting the results, we explicitly consider these limitations, and this study relies on relative patterns among countries rather than absolute values.

This analysis faces several constraints. The cross-sectional design cannot make causal inferences; the correlations may reflect Chinese firms' self-selection of favorable institutional environments rather than the impact of institutions on collaboration. The small sample size (N = 27) limits the ability to test for moderate effects, especially with respect to FDS. While the four-category clustering scheme is theoretically reasonable, it includes a cluster containing only three countries (cluster 2), which reduces the reliability of comparisons of means involving this group.

4.8 Summary

The structural analysis in this chapter establishes the IPR-IPA combination as a core condition for high CPI, but it does not yet answer how these institutional combinations evolve over time, or how firm-level decision-making mechanisms mediate national-level connections. Chapter 5 will integrate these findings and discuss their theoretical and policy implications.

Conclusions

This study examines how the configuration of innovation-related institutional environments in 27 EU member states correlates with the intensity of China-EU co-inventor patents during the period from 2016 to 2022. Employing a descriptive cross-sectional exploration approach and relying entirely on publicly available data, the study identifies four distinct country institutional profiles through hierarchical cluster analysis. The results show that, across all institutional configurations studied, stronger intellectual property protection and a higher degree of alignment between host country industrial policy priorities and China's strategic sectors are positively correlated with higher intensity of co-inventor patents. In contrast, general economic development indicators such as GDP per capita and R&D expenditure have negligible explanatory power. The institutional configuration patterns further indicate that a combination of strong intellectual property protection and high industrial policy alignment creates the most favorable environment for observable non-equity knowledge integration; while institutional configurations characterized by substantial state aid and stringent FDI screening are often associated with lower collaborative activity.

These findings expand upon two key theoretical perspectives in the fields of international business and innovation management. First, these findings support and refine Kostova's (1999) institutional duality framework, demonstrating how host country institutional pressures influence the entry mode choices of Chinese companies, prompting them to shift towards lighter, more collaborative technology acquisition methods when facing greater obstacles in equity-based entry. The results also significantly refine Dunning's (1993) OLI paradigm: research shows that the pursuit of crucial locational advantages for strategic assets stems less from large market or economic size and more from specific policy areas, particularly the alignment of intellectual property enforcement and industrial policies. This study uses co-inventor patents as a measurable indicator of the shift towards light-asset entry modes and considers it as an explanatory perspective, thus further enriching its conceptual contribution.

These patterns imply to EU policymakers that strengthening intellectual property enforcement and clarifying industrial policy priorities can enhance a country's attractiveness to international collaborative innovation. While this study does not evaluate specific policy tools, the observed patterns point to a practical consideration: distinguishing between high-risk equity acquisitions and low-risk collaborative arrangements may be necessary. This information is equally relevant for Chinese technology companies. The findings underscore the importance of thorough institutional due diligence and point to countries with strong intellectual property protection and aligned industry priorities as ideal locations for R&D collaboration.

This study has some limitations. The cross-sectional design and small sample size (N=27) limit causal inferences and statistical power, particularly in testing intermediate or interaction effects. Because the analysis relies on national-level patent aggregation data, it inevitably masks heterogeneity and informal knowledge exchange at the firm level. Furthermore, the study is descriptive in nature, meaning some associations may partially reflect self-selection: partners from China may have initially favored institutionally favorable environments.

Despite these limitations, this study provides a transparent and replicable foundation for examining institutional frictions in China-European knowledge integration. A longitudinal research design would be a logical next step, allowing researchers to trace how the evolution of FDI screening mechanisms since 2019 has shaped collaboration patterns over time. Incorporating firm-level perspectives or evidence based on qualitative research such as interviews would help reveal the underlying micro-mechanisms, while extending this structural perspective to other emerging economies would help test the broader applicability of the argument. As geopolitical tensions play an increasingly important role in the global technology flow structure, a clearer understanding of the institutional conditions that promote or hinder collaborative innovation is both timely and crucial for policymaking.

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Appendix A. Supplementary Tables and Robustness Checks

Methodological Reference (A1 – A2):

Table A1

Percentile Thresholds for Institutional Variable Classification (N = 27 EU Member States)

Variable	33rd Percentile	67th Percentile
IPR	68.5	79.2
RDT	0.115	0.198
SA	1.32	3.21
IPA	8.7	10.4
FDS	0.85	2.05

Notes. IPR = Intellectual Property Rights (Heritage Foundation Property Rights score, 0–100). RDT = R&D Tax Incentives (1 minus B-Index). SA = State Aid for R&D&I as % of GDP. IPA = Industrial Policy Alignment (count of overlapping strategic sectors, range 7–12). FDS = FDI Screening Strictness (0–3 scale). All percentiles are calculated from the averaged values over 2016–2022, except FDS which uses the shorter 2020–2022 window following the implementation of the EU screening framework. For each variable, scores below the 33rd percentile are classified as low, between the 33rd and 67th percentiles (inclusive) as moderate, and above the 67th percentile as high. These thresholds are applied consistently across all cluster profiles (Table 2) and descriptive interpretations.

Table A2

Cluster Mean CPI Comparison

Cluster	Cluster Name	Countries (n)	Main Period (2016–2022) Mean CPI	2020–2022 Mean CPI	Change
1	Peripheral mixed	10	0.85	0.79	↓
2	Eastern transition	3	0.58	0.7	↑
3	Nordic/Western core	7	19.79	21.85	↑
4	Continental/mixed	7	2.92	3.48	↑

Configurational Analysis Details (A3 – A5)：

Table A3

Conditional Mean Collaborative Patenting Intensity by High/Low IPR and High/Low FDI Screening

Configuration	FDS Low	FDS High	n (Low/High)
High IPR	11.47	13.94	8/5
Low IPR	0.39	0.86	8/6

Table A4

Conditional Mean Collaborative Patenting Intensity by High/Low SA and High/Low FDI Screening

Configuration	FDS Low	FDS High	n (Low/High)
High SA	1.76	1.33	7/6
Low SA	9.18	13.37	9/5

Table A5

Three-Way Configurational Analysis: IPR × IPA × FDS

IPR	IPA	FDS	Mean CPI	n
Low	Low	Low	0.36	6
Low	Low	High	0.52	2
Low	High	Low	0.51	4
High	Low	Low	6.27	6
High	Low	High	3.22	2
High	High	Low	27.09	2
High	High	High	21.08	3

Regression and Robustness Evidence (A6－A11)：

Table A6

Model Selection based on Information Criteria (AIC and BIC)

Rank	Model Specification	AIC	BIC	Adj. R^2
1	IPR + IPA + RDT + GDP_pc + GERD	203.9	211.68	0.393
2	IPR + IPA + FDS + GDP_pc + GERD	204.72	212.5	0.374
3	IPR + IPA + GDP_pc + GERD (Preferred Model)	206.41	212.89	0.316
4	IPR + RDT + GDP_pc + GERD	206.85	213.33	0.304
5	IPR + GDP_pc + GERD	207.42	212.61	0.268
6	IPR + IPA + SA + GDP_pc + GERD	207.71	215.49	0.301
7	IPR + RDT + SA + GDP_pc + GERD	208.84	216.61	0.271
8	IPR + RDT + FDS + GDP_pc + GERD	208.85	216.62	0.271
9	IPR + FDS + GDP_pc + GERD	209.07	215.55	0.245
10	IPR + SA + GDP_pc + GERD	209.34	215.82	0.237

Table A7

Supplementary OLS Regression Models (N=27)

Variables	Model 1 (Main)	Model 2 (IPR+FDS)	Model 3 (RDT+SA)	Model 4 (IPR+IPA+FDS)

IPR	0.668**	0.702**	-	0.611**
IPA	2.136*	-	-	3.523**
FDS	-	-1.23	-	-4.296
RDT	-	-	-26.464	-
SA	-	-	-1.909*	-
GDP_per_capita	0	0	0	0
GERD	0	0	0	0
Constant	-65.278**	-46.670**	12.547**	-69.459**
R²	0.421	0.361	0.172	0.495
Adjusted R²	0.316	0.245	0.021	0.374

Notes. Heteroskedasticity-robust standard errors are reported.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed).
Model 1 is the main specification. All models serve only as supplementary evidence due to the small sample size (N=27).

Table A8
Supplementary OLS Regression Results Using 2020–2022 Window Only

Variables	Model 1 (Main)	Model 2 (IPR+FDS)	Model 3 (RDT+SA)	Model 4 (IPR+IPA+FDS)
IPR	0.743 (0.309)**	0.788 (0.359)**	-	0.689 (0.293)**
IPA	2.539* (1.578)	-	-	3.856 (1.799)**
FDS	-	-0.723 (2.655)	-	-4.079 (2.677)
RDT	-	-	-30.465 (21.866)	-
SA	-	-	-2.062 (1.084)*	-
GDP_per_capita	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
GERD	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-74.048 (33.977)**	-53.076 (26.264)**	14.061 (7.348)*	-78.018 (33.240)**
R²	0.412	0.34	0.165	0.464
Adjusted R²	0.305	0.22	0.014	0.336

Notes: Heteroskedasticity-robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed).
All variables are averaged over the 2020–2022 period only.

Table A9

VIF Diagnostics (Model 1 - Main)

Variable	VIF
IPR	1.17
IPA	1.33
GDP_per_capita	1.06
GERD	1.38

Notes. The constant term is not shown. All predictor VIF values are well below 5, indicating no serious multicollinearity. HRST was excluded due to high correlation with GERD.

Table A10

Robustness Check: Correlation Coefficients Across Temporal Windows

Variable	Main Analysis (2016–2022)	2020–2022 Window	Difference	Notes
IPR	0.581***	0.576***	-0.005	Very small change
IPA_overlap_count	0.371*	0.359*	-0.012	Very small change

Notes. Main analysis uses averaged variables over 2016 – 2022.
2020 – 2022 window uses yearly co-patent counts and yearly population data to compute precise CPI, while other institutional variables remain the same as in the main analysis.
*** p < 0.01, * p < 0.10 (two-tailed).
Differences are minimal, indicating high temporal stability of the main findings.

Table A11

Robustness Check: Tertile Calibration (High IPR × High IPA)

IPR (Tertile)	IPA (Tertile)	Low CPI	Medium CPI	High CPI
0	0	0.268	1.081	9.201
0	1	NaN	1.068	11.678
1	0	0.216	3.917	16.482
1	1	NaN	NaN	25.783

Notes. NaN indicates no observations in this cell.

Résumé

Institutsionaalsed konfiguratsioonid ja Hiina–EL koostöölise patenteerimise intensiivsus: innovatsiooniga seotud institutsionaalsete hõõrdumiste eksploratiivne kvantitatiivne analüüs Euroopa Liidus

Jingsong Yang

Käesolev magistritöö uurib, kuidas innovatsiooniga seotud institutsionaalsete tingimuste konfiguratsioonid 27 Euroopa Liidu liikmesriigis on seotud Hiina–EL koostöölise patenteerimise intensiivsusega ajavahemikul 2016–2022. Uurimus lähtub eksploratiivse kvantitatiivse kirjeldava läbilõikeuuringu disainist ning tugineb üksnes avalikult kättesaadavatele andmetele.

Töö teoreetiliseks aluseks on kolm raamistikku. Dunningi eklektiline OLI paradigma selgitab asukoha eeliseid teadmistemahukate tegevuste puhul. Kostova institutsioonilise dualiteedi teooria näitab, kuidas kodu- ja vastuvõtjariigi institutsionaalsed surved suunavad ettevõtteid valima kergemaid koostöövorme, kui omakapitalipõhine turulepääs muutub raskemaks. Mitte-omakapitalivormide kirjandus käsitleb ühispatenteerimist kerge varalise kuluga rahvusvahelise koostöö väljundina. Nendest raamistikest lähtuvalt tõlgendatakse töös Hiina–EL ühispatente kui ettevõtete turulepääsuviiside kohandamise mõõdetavat indikaatorit.

Analüüs hõlmab viit institutsionaalset tingimust: intellektuaalomandi õiguste kaitse tugevus, teadus- ja arendustegevuse maksusoodustuste suuremeelsus, riigiabi kättesaadavus, välismaiste otseinvesteeringute (VOI) sõelumisstriktsus ning tööstuspoliitika kooskõla Hiina strateegiliste sektoritega. Koostöölise patenteerimise intensiivsus arvutatakse OECD patentistatistika andmete põhjal ja normaliseeritakse elanikkonna suuruse järgi, et tagada riikidevaheline võrreldavus.

Analüüs viiakse läbi nelja etapis. Hierarhilise klasteranalüüsi (Wardi meetod) abil tuvastatakse neli erinevat institutsionaalset profiili. Seejärel uuritakse tingimuste kahekaupa seoseid, konfiguratsioonilist ristanalüüsi ja täiendavat regressioonmudelit.

Robustsuskontrollid hindavad tulemuste stabiilsust alternatiivsetes ajavahemikes ja mudeli täpsustustes.

Tulemused näitavad, et tugevam intellektuaalomandi kaitse ja suurem tööstuspoliitika kooskõla Hiina strateegiliste sektoritega on järjepidevalt positiivselt seotud kõrgema koostöölise patenteerimise intensiivsusega. Kõige kõrgem keskmine intensiivsus esineb riikides, kus mõlemad tingimused on tugevad – eeskätt Põhja- ja Lääne-Euroopas. Üldised majandusarengut iseloomustavad näitajad, nagu SKP elaniku kohta ja teadus-arendustegevuse kulutused, on koostöölise patenteerimisega vähese seletavusvõimega. VOI sõelumise mõju osutub konfiguratsioonisõltuvaks: range sõelumine kombineeruna nõrga intellektuaalomandi kaitsega on seotud madalama koostöölise intensiivsusega, samas kui tugev intellektuaalomandi kaitse võib sõelumise pärssivat mõju leevendada.

Töö panustab rahvusvahelise äri ja innovatsioonijuhtimise kirjandusse kolmel viisil: tutvustab ühispatenteerimise intensiivsust kerge varalise kuluga turulepääsuviisi proksi-mõõdikuna, pakub süstemaatilise institutsionaalse kaardistuse kõigi 27 EL liikmesriigi kohta sihipäraste innovatsioonipõhiste näitajate abil ning rakendab konfiguratsiooniperspektiivi, mis läheb kaugemale tavapärastest aditiivsetes lähenemistest. Piirangutena tuleb märkida, et läbilõikeuuringu disain välistab kausaalsed järeldused ning väike valimimaht (N=27) piirab statistilist jõudu. Tulevased uurimused võiksid kaasata pikisuunalise analüüsi, ettevõttetaseme andmeid ning laiendada konfiguratsioonilise lähenemise teistele arenevate majanduste kontekstidele.

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