



1506
UNIVERSITÀ
DEGLI STUDI
DI URBINO
CARLO BO

UNIVERSITÀ DEGLI STUDI DI URBINO CARLO BO

Department of Economics, Society, Politics

Ph.D. PROGRAMME IN: Global Studies. Economy, Society and Law

CYCLE: XXXVII

Functional Positioning and Innovation in GVCs

Evidence from European Industries

ACADEMIC DISCIPLINES:

ECON-01/A Economics | ECON-02/A Economic Policy | STAT-02/A Economic Statistics

Coordinator: Prof. Giovanni Marin

Supervisor: Prof. Antonello Zanfei

Supervisor: Prof. Andrea Coveri

Ph.D. student: Omar Abdelhamid Hussein Talaat Elzoheiry

ACADEMIC YEAR
2023/2024



Functional Positioning and Innovation in GVCs

Evidence from European Industries



Table of Contents

<u>General Introduction</u>	<u>4-6</u>
<u>Chapter 1 Innovation in Global Value Chains</u>	<u>7-44</u>
Section 1.1: Introduction	
Section 1.2: Innovation in the GVC Framework	
Section 1.3: Is Innovation a Capacity or an Outcome?	
Section 1.4: The Role of Governance in GVCs	
Section 1.5: The Role of Intangible Assets in GVCs	
Section 1.6: Functional Specialization of Industries and Innovation Capacity	
<u>Chapter 2 Summary Statistics</u>	<u>45-73</u>
Section 2.1: Introduction	
Section 2.2: Data Strategy: FDI Markets and SID Merger	
Section 2.3: Stylized Summary Statistics: Distribution of Inward FDIs	
Section 2.4: Stylized Summary Statistics: Innovativeness by Time, Country, and Industry	
<u>Chapter 3 Innovation and Functional Specialization of EU Industries</u>	<u>74-124</u>
Section 3.1: Introduction	
Section 3.2: EU Functional Specialization Profiles—FSP (FDI Data)	
Section 3.3: Functional Specialization and Innovation Propensity of European Industries	
Section 3.4: Functional Diversification and Innovation Propensity of European Industries	
<u>Chapter 4 The Link Between Functional Upgrading and Innovation in GVCs</u>	<u>125-149</u>
Section 4.1: Introduction	
Section 4.2: Change and Continuity in FSPs of EU Industries	
Section 4.3: The Paradox of Progress in Upgrading and Innovation	
<u>Chapter 5 Conclusions and Policy Recommendations</u>	<u>150-166</u>
Section 5.1: Overview and Summary of Findings	
Section 5.2: Theoretical and Empirical Contributions	
Section 5.3: Limitations and Implications for Future Research	
Section 5.4: Policy Recommendations	
Section 5.5: Final Reflection on European Economic Sovereignty	

General Introduction

This dissertation investigates the relationship between functional specialization and innovation propensities within European industries embedded in global value chains (GVCs). The global economic landscape has transformed, characterized by fragmented production processes and increased reliance on intangible knowledge assets (IKAs). Within this context, understanding how industry positioning within GVCs foster or hinder innovation is crucial for academic inquiry and policy formulation.

Motivation

Owing to conceptual confusions within the Innovation literature itself, existing GVC scholarship often inadequately conceptualizes and measures innovation, frequently conflating it with expenditure on technology or R&D or inferring it from positional changes without observing a direct change in endogenous capabilities as a result of this change. This overlooks nuanced mechanisms through which innovation emerges as an organizing principle of global production.

This research addresses this gap by adopting an interactive model of innovation, shifting the analytical focus from product-based to function-based competition. It posits that innovation gains are not merely a by-product of GVC participation but rather directly shaped by functional position of the participating firm. The rising centrality of IKAs—such as design capabilities, data, organizational routines, and relational capital—underscores the necessity of this functional perspective, as these assets underpin competitive advantage.

Research Questions

This dissertation addresses the following core research questions:

1. Do specific functional positions within GVCs exhibit a greater propensity for innovation at the industry level, and if so, which positions are these?
2. How does functional diversification within industries relate to innovation capacities, and are these relationships consistent across economic sectors?
3. How do patterns of functional change—specifically functional entry and exit—impact innovation propensities over time, and does "upgrading" always correlate to innovation benefits?
4. What factors influence the efficacy of functional positions and diversification in fostering innovation, and how do these dynamics vary across different technological regimes or industry types?

Methodological Approach and Data Sources

The empirical investigation translates these conceptual propositions into a measurable strategy by integrating two primary datasets: FDI Markets (FDI-M) and the Sectoral Innovation Database (SID). FDI-M records greenfield investment projects, serving as a proxy for functional positioning

in GVCs by reflecting the allocation of technologically embodied and knowledge-intensive tasks across borders. The Functional Specialization Index (FSI), derived from Balassa's (1965) concept of revealed comparative advantage, operationalizes functional specialization. The SID provides industry-level innovation indicators. The merged SID-FDI dataset covers 38 manufacturing and service industries across five European economies—Germany, France, Italy, Spain, and the Netherlands—from 2003 to 2016. To capture longitudinal dynamics, the analysis in Chapter 4 tracks structural changes across four distinct periods, allowing for the observation of functional entry, exit, and deepening.

Highlights of Main Findings

The empirical analysis reveals that industries specializing in pre- and post- production functions demonstrate higher innovation rates compared to those focused on production functions, extending the “smile curve” hypothesis from value-added to innovation performance. Higher functional diversity is associated with stronger innovation outcomes, particularly in product innovation, a relationship robust even after controlling for industry and country-specific factors. This positive effect of functional diversification on innovation is statistically significant only in service industries, not in manufacturing. Crucially, the longitudinal analysis shows that functional “upgrading” is not associated with higher innovation rates in the short term. Industries characterized by functional “deepening”—the persistence and entrenchment of a specialization over the long time, however, do exhibit higher innovation propensities than those undergoing frequent structural change, regardless of the direction of this change. This suggests that the process of changing functional profiles can be disruptive, creating “bumps in the road” that temporarily impede innovation capacity.

These findings demonstrate the link between innovation capacity and functional position of industries within GVCs, and that functional diversity and deepening are sources of innovative advantage. The research underscores that functional change is not a linear path to improvement; rather, the stability and embeddedness of specialized capabilities are critical for sustained innovation. This dissertation provides a framework for understanding the interplay between GVC participation, functional specialization, and innovation in the European Union, offering insights for academic discourse and policy development aimed at fostering industrial upgrading and competitiveness.

Contributions

This research offers substantive contributions to the theory and empirical analysis of innovation in GVCs, intersecting Economics, Evolutionary Economic Geography, innovation studies, and International Business. Theoretically, it advances a conceptualization of innovation dynamics by centering on functions, rather than products, as the fundamental analytical unit of competitiveness. It highlights the centrality of intangible assets and the changing role of innovation within GVCs. A significant contribution is empirical distinction between “upgrading” and “innovation,” showing they are discrete processes that can move in opposite directions. Empirically, the dissertation provides original quantitative evidence, extending the “smile-curve” hypothesis to innovation performance. It also provides a nuanced understanding of how functional diversification and functional deepening impact innovation, revealing sector-contingent effects, particularly the stronger association between diversification and innovation in service industries.

Policy Implications

The policy implications of this dissertation are twofold. First, the evidence calls for a decisive shift in EU innovation and industrial policy away from product-based thinking toward a functional perspective that recognizes the differentiated innovation effects of different GVC positions and different positional changes. Across the industries examined, preproduction and postproduction functions are systematically associated with stronger innovation propensities than production functions, confirming that the “smile curve” is not merely a value-capture device but that it is also relevant to innovation capacities. Yet Chapter 4 adds a crucial refinement: functional change is not inherently beneficial, and the presumed virtues of upgrading should not be overstated. In several cases, industries that altered their functional profile did not outperform those that maintained continuity; indeed, the empirical patterns suggest that functional deepening and diversification may be more conducive to sustained innovation than repeated oscillation across functions, even if those functions are of the highest value (eg. R&D). Policy should therefore focus less on abstract upgrading and more on capability accumulation, supporting the consolidation of intangible knowledge assets, the retention of function-specific expertise, and the gradual strengthening of those activities in which firms and regions already possess revealed strengths.

Second, these findings speak directly to the architecture of existing EU instruments, particularly Smart Specialization Strategies, Horizon Europe Missions, and the European Innovation Council. The European Commission already frames Smart Specialization as a place-based approach built on localization, prioritization, and stakeholder participation, while Horizon Europe programs mobilize research and innovation around environmental and societal goals, and the EIC supports breakthrough innovation and scale-up across the lifecycle. However, the dissertation suggests that these frameworks would be more effective if they incorporated a functional logic: regions should not only identify the sectors in which they are active, but the specific functions they perform competitively, the combinations of functions that generate learning spillovers, and the intangible capabilities required to move into higher-value positions without sacrificing innovation performance. This is especially important in services, where functional diversity appears to be a stronger driver of innovation than in manufacturing, and where policy can most effectively stimulate cross-functional recombination, knowledge spillovers, and the financing of intangible investments. In this sense, the thesis supports a more nuanced and strategically demanding policy agenda: one that treats innovation as embedded in functional structure, constrained by largely exogenous institutional conditions, and sustained through the disciplined accumulation of capabilities rather than as an assumed outcome.

Chapter 1 | Innovation in Global Value Chains

1.0 | Executive Summary and Chapter Roadmap

This chapter examines how participation in Global Value Chains (GVCs) shapes innovation, arguing that understanding this relationship requires moving beyond conventional approaches that equate innovation with upgrading or treat GVC participation as inherently beneficial. While the GVC framework has been instrumental in explaining the fragmentation of production and the emergence of globally dispersed systems of value creation, its treatment of innovation has often remained conceptually ambiguous.¹ In particular, the tendency to conflate innovation with productivity gains, learning, or upgrading has generated conceptual imprecision, mixed empirical findings, and potentially misleading policy implications.

To address this issue, the chapter proposes a conceptualization of innovation as a firm's enduring propensity or capacity to generate, absorb, adapt, and embed novelty, rather than merely as a discrete observable event or outcome. **This distinction is crucial because upgrading within a GVC—while often reflecting an improved position in production networks—does not necessarily imply a strengthening of endogenous innovative capabilities. Firms may upgrade without developing the underlying capabilities required for sustained technological change, while meaningful gains from GVC participation may also emerge through the accumulation of knowledge and problem-solving abilities extending beyond the immediate requirements of participation itself.**

Innovation capacity, in turn, is understood as being shaped by a combination of technological, organizational, and institutional factors. Technological regimes characterized by irreversibility, path dependency, and lock-ins define the opportunities and constraints facing firms. GVC governance structures influence the extent to which firms can access knowledge, participate in learning processes, and accumulate capabilities. National Systems of Innovation (NSIs) further shape these dynamics by providing the broader institutional ecosystem through which knowledge is generated, diffused, and applied.

Building on insights from GVC governance, Evolutionary Economic Geography, and the literature on Intangible Knowledge Assets (IKAs), the chapter argues that the effects of GVC participation on innovation depend not simply on participation itself, but on the specific functions performed within value chains. Accordingly, the analysis shifts from a traditional product-based understanding of specialization toward a function-based perspective that foregrounds the activities undertaken by firms. This approach highlights how value creation and capture are unevenly distributed across GVC functions, with intangible-intensive upstream activities (e.g. R&D and design) and downstream activities (e.g. branding and marketing) generally associated with greater opportunities for learning, capability accumulation, and value appropriation than fabrication and assembly.

In this perspective, functional specialization becomes a key analytical lens through which to understand heterogeneous innovation capacity changes in GVCs. **A firm's capacity to accumulate and deploy intangible knowledge assets influences its ability to navigate governance asymmetries, benefit from local and sectoral spillovers, and engage in cumulative processes of functional upgrading.** Functional upgrading therefore emerges as a path-dependent process closely linked to innovation capacity rather than to GVC participation per se.

¹ As is stated repeatedly throughout this chapter, the conceptual confusion surrounding 'innovation' is not inherent or exclusive to the GVC literature, instead arising from the innovation literature itself and exasperated in the GVC context given the overlap between 'innovation' and 'upgrading'.

Finally, the chapter motivates an industry-level perspective to account for horizontal knowledge diffusion and sector-specific dynamics that firm-level approaches may overlook. This conceptual framework provides the foundation for the empirical analysis that follows. The next chapter introduces the data and measures used to examine how patterns of functional specialization are associated with innovation outcomes across industries in several European economies.

1.1 | Introduction

The Global Value Chain (GVC) framework—initially called Global Commodity Chain (GCC; Hopkins & Wallerstein, 1994)—is an approach used to study the global economy in the form of networks of relationships featured by power asymmetries and made up of geographically dispersed firms of different sizes, showing heterogeneous productive specializations (Gereffi, 2014: 10). The framework is developed in response to the increase in the fragmentation of production witnessed in the last 50 years, characterized by a decline in single-nation supply chains and a marked increase in offshoring and outsourcing, rendering ‘gross exports’ a significantly less viable measure of an economy’s trade integration and international economic relevance.

Over the past three decades, and spread across the disciplines of Economics, Economic Sociology, Political Economy, Developmental Studies, and International Business (IB), GVC scholars have examined the rise of global value chains from several angles echoing their disciplinary diversity.

Business scholars, commonly in qualitative studies, have focused (mainly but not exclusively) on the issue of governance (Kano et al., 2020; Strange & Humphrey, 2019), wherein a “lead firm” (commonly a multinational—MNE) and large buyers leverage disproportionate economic power to control the distribution of the proverbial economic pie. Different typologies of governance based on structural and institutional factors were linked to firms’ abilities to capture value from participation in GVCs (Gereffi et al., 2005 & Gereffi, 2019). Also within the IB remit are matters of geographical location (commonly dichotomizing and comparing value capture in ‘headquarters’ and ‘factory’ locations) and GVC dispersion (Inomata et al., 2015; Kali et al., 2016; Brandl et al., 2017), the formation of local clusters (Bair & Gereffi, 2001), locational patterns and industry dynamics (Fernandez-Stark & Gereffi, 2019), and the monopolization of knowledge by lead firms (Pagano, 2014; Dallas et al., 2019).

Quantitative GVC studies levy econometrics to demonstrate patterns, relating to country, industry, or firm level determinants of GVC participation (Looi et al., 2022); the accounting of trade flows within GVCs based on World Input-Output Tables—WIOTs (Miller & Blair, 2009; Antras & Chor, 2021); productivity gains arising from participation (Timmer, 2017); and the process and depth of ‘upgrading’ arising from participation (Fuentes & Pipkin, 2017), although it has been largely noted in the literature that there is a lack of agreement as to how to empirically measure upgrading (Van Assche & Van Biesebroeck, 2018). Also elusive are measures of governance and how it interacts with upgrading (Kim et al., 2020), although quantitative studies on the topic have been conducted (De Marchi et al., 2018; Pietrobelli & Saliola, 2008).

In 2020, the OECD reported that as much as 70% of all value in international trade is used for production in global value chains (OECD, 2020). The OECD recommended a shift in national trade policies worldwide, specifically to “cover as many dimensions of GVCs as possible, from customs barriers to rules of origin to trade facilitation to services” (ibid, 1).² It is, thus, critical to examine if indeed (and under what conditions) the GVC framework captures gains from specialization in trade. Ultimately, one can even argue the fact of these gains matters less to a nation than their scientific understanding of the sources of these gains. After all, it is the latter that will form the basis of the policies upon which future GVC trade will occur. In other words, our understanding of *where* the benefits come from is key to their continuation.

A novel fork in GVC research evolves alongside this concern over our understanding of the object to which returns from trade accrue. Classically, product-based frameworks posit the *output* of a firm—the *thing* being traded—as the object of specialization. Quality, cost, and other aspects

² This is despite noting that since 2011, GVC integration has been declining

related to the output of a firm are the units of analysis that determine degree of and return to specialization.

In this view, for example, one can say the Netherlands has been more specialized than Spain in computer manufacturing (industry code C26³) in the 21st Century. This is because C26 in Spain only averaged around 3% share of total Spanish exports in the first 15 years of the 21st Century as compared to the Dutch C26 export share of ~ 12%. One may choose to further break down C26 into sub-products, and researchers can compare the returns in that manner. For example, Spanish companies working in the computer manufacturing industry tended, in the same time period to specialize in communication equipment (C26.3) and electronic components (C26.1), while their counterparts in Holland specialize in semiconductor machinery (often categorized also under C26.1 or related machinery codes), high-end computers, and peripheral equipment. A lot can be gained from product-based views of GVC trade.⁴

However, the primary reason Dutch firms command higher returns becomes clearer when adopting a function-based view of trade, which places centrefold the activities of capital and the labour in the exporting company. While C26 is a manufacturing industry, Dutch companies in that industry specialize in logistics and headquarter functions rather than the much more common manufacturing specialization in C26. That is, they tend to export a less common, more complex intangible service.

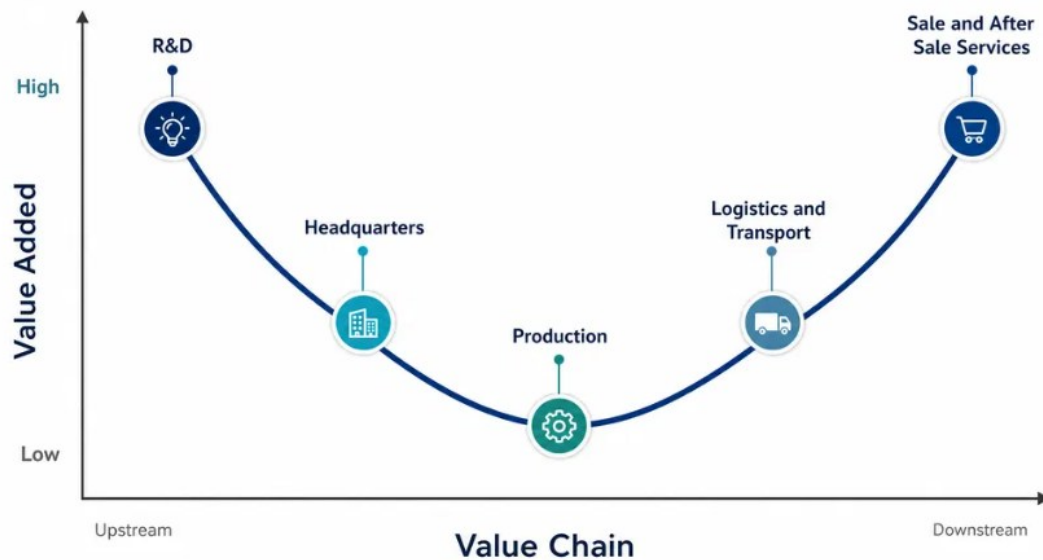
Their counterparts in Spain—Spanish firms in C26—are specialized in an entirely different function: manufacturing of telecom components, a highly tangible function marked by an abundance of competitors and, thus, low-road price competition that shrinks profit margins (Durand & Milberg, 2020). Thus, it is not that Dutch firms produce more sophisticated components, but that they perform a more sophisticated function than their Spanish counterparts within the value chain. The importance of this distinction is at the heart of this research.

Returns to trade, by function, are illustrated by the Smile curve, which has become emblematic of the functional lens in GVC scholarship:

³ All industry codes and subindustry codes used throughout all pages of this research are Nace Rev. 2 industry codes

⁴ All data presented, unless directly stated otherwise, comes from the Sectoral Innovation Database (SID) and the FDI Markets (FDI-M). These databases are introduced and analyzed in the next chapter.

Figure 1. Smile Curve (author's own rendition)



The smile curve hypothesis asserts that value creation and appropriation within Global Value Chains (GVCs) concentrate in intangible-intensive upstream and downstream segments (e.g. R&D, design, & marketing), diverging from tangible-intensive fabrication and assembly. This generates pronounced asymmetries in 'value capture', challenging the assertion that GVC participation benefits developing economies.

This hypothesis necessitated novel trade models and statistical frameworks. Chen, Los, and Timmer (2018) demonstrate that approximately one-third of GVC value derives from intangible assets, a proportion exhibiting consistent growth, particularly in technology, branding, and design. Existing growth accounting models inadequately capture intangible expenditures. Corrado, Hulten, and Sichel (2005, 2009) reveal that excluding intangible expenditures significantly underestimates capital stock, distorting insights into labor productivity and economic theory.

New statistical methodologies quantify economic geography's specialization in intangibles. Timmer et al. (2019) incorporate occupational structure into revealed comparative advantage (Balassa, 1965) indicators, demonstrating a negative (positive) relationship between economic growth and specialization in fabrication (research and development) activities. Coveri and Zanfei (2022) compute Functional Specialization in FDI, a Balassa (1965) index, showing that specialization in intangible-intensive functions correlates with greater value capture from GVC trade, supporting the smile curve hypothesis. This functional lens, while elucidating specialization-value hierarchies, now extends to macroeconomic innovation dynamics, enabling robust macroeconomic hypothesis testing regarding intangible assets and innovation.

Mudambi (2008) formalized the smile curve with reference to 'electronics' GVCs, illustrating how design and branding concentration yields disproportionate returns relative to assembly. Case studies corroborate this pattern: pharmaceutical GVCs exhibit R&D and control retention by European and North American firms with outsourced production (Pisano & Shih, 2012); automotive GVCs show German firms anchoring innovation with Eastern European assembly (Sturgeon & Van Biesebroeck, 2011); and the European textiles sector concentrates design in Italy and France, with production in North Africa and Asia (Gereffi & Frederick, 2010). This functional approach integrates insights from urban and economic geography concerning function co-location

and agglomeration, addressing product classification limitations that mask functional heterogeneity and spatial specificity in trade flows.

1.2| Innovation in the GVC Framework

At the heart of many GVC investigations are the related concepts of ‘innovation’, ‘technology’, ‘productivity’, and ‘upgrading’, and their change over time. These concepts are linked to notions of firm (re)location decisions, governance, MNE power, firm productivity, and more. They are linked insofar as GVC frameworks investigate economic trade and growth, in which these concepts are embedded; but they are also linked insofar as GVC participation in and of itself is perceived to increase firm innovation capacity in unique ways that extend beyond traditional trade theory. Indeed, as will be shown throughout this dissertation, there is no shortage of case studies claiming, ‘GVC participation is favourable for innovation’.

Simultaneously, other scholars have noted that the systematic study of innovation is markedly absent from the GVC literature. Some have even identified “the missing conceptualization and empirical investigation of the process of learning” as a shortcoming in GVC literature (Lema et al., 2018: 347). **This problem is not exclusive to the GVC literature and instead occurs as a result of existing conflation surrounding the term, innovation, from within that scholarship.** As a result, the GVC literature tends to contain ‘innovation’ within the concept of ‘upgrading’, which can refer to (Humphrey & Schmitz, 2002):

- Product upgrading → offering a product associated with higher value capture
- Process upgrading → producing the same product, but more efficiently
- Functional upgrading → increasing overall ‘skill content’ by performing new and better (higher value capture) functions entirely
- Chain upgrading → a move to new industries

The interaction between the two notions is notoriously murky. Initially, they may seem to be synonyms. A seminal 2008 contribution by Morrison, Pietrobelli, and Rabellotti underscores the point:

[T]he concept of upgrading suffers from some logical contradictions: it is used as a synonym for innovation, yet it is also intended as the outcome of an innovation process. [...] [T]he two concepts [...] frequently overlap and are used interchangeably, [...] [I]n most of the empirical analyses there is no systematic attempt to investigate learning and innovation at the firm and cluster levels. When upgrading is identified, it is often stressed that this is the outcome of some activity aimed at building capacity; yet this activity is at best only mentioned, never fully examined. Such an attitude hampers an analytical treatment of the concept, and besides, it may lead to misleading policy suggestions, as it assumes the presence of upgrading whenever a “good” outcome emerges from a buyer – producer interaction (Morrison et al., 2008: 45).

The result of this conflation is not esoteric: when “upgrading” is simultaneously treated as a synonym for and outcome of innovation, any intellectual inquiry is hindered, empirical results are muddled, and policy recommendations are misguided.⁵ Increasingly, GVC studies are adopting

⁵ Moreover, this blending of concepts leads to contaminated numbers: since the measure of upgrading is in terms of the ‘per unit value’ of products or services, then the term also captures ‘marginal’ increases resulting from short term

more flexible definitions of upgrading as a two-way process in which firms may experience both upgrading and downgrading (for example, see Blazek, 2016) without the assignment of a normative connotation to either process; and in terms of dimensions beyond economic performance, including environmental and social aspects (for example, see Bernhardt and Pollak, 2016).

To illustrate the confusion between upgrading and innovation, consider the case of Indonesian consumer electronics firms (domestic and joint ventures), which supply and assemble for Japanese leaders like Toshiba and Panasonic in Global Value Chains. After GVC participation and direct training by MNEs and larger buyers, the firms demonstrated a shift from conveyor-belt assembly to cell production systems, boosting productivity, multitasking, and flexibility while adopting Kaizen and PDCA continuous improvement methods (Kadarusman, 2012).

In addition to these on-chain improvements, companies like Pusaka Elektrindo and Harapan Elektrindo now adapt products for developing powerful speaker technology and advanced antenna systems tailored for the weak transmitters (ibid), a problem in their local market (off-chain) that had been unsolved until they introduced these advanced antennas (ibid).

From the above example, it is easy to describe where the confusion might come from. Is the transition from an old conveyor belt to the newer, cell production system an example of process innovation? It is clearly an upgrade to the position of the firm within the GVC to which it belongs. However, this would mean upgrade is synonymous with innovation, diluting the analytical utilities of both concepts.

If they are not synonymous, is innovation then the transformation process from old to new (an outcome)? and is upgrading the result of that process on the position of the firm in the GVC? If so, it would follow that upgrading was guaranteed given the productivity changes arising from training and new technology adoption, which would suggest those ‘events’ are the innovative process, which is also not accurate.

Not only do murky definitions cause problems for the study of innovation in GVCs, but also more generally in that field: Morrison et al (2008) note that the confusion belying the notion of upgrading is the primary culprit for a common and dangerous misconception and oversimplification in the literature: the idea that GVCs are linear—i.e. upgrading ‘crowds out’ deepening:

A vivid way of illustrating this concept has been the description by several authors of upgrading within a value chain as “going up the value ladder”, moving away from activities in which competition is of the “low road” type and entry barriers are low. However, although this description is certainly eye-catching and has some advantages, it is not very accurate. GVCs are hardly as linear as they are often described; indeed, this assumed linearity [...] drives attention away from all the detailed and equally important efforts to build and deepen [technological capabilities] at the same stage of the value chain. We argue that the key issue is not always “functionally upgrading” and moving into more advanced functions “along the value chain”, but often deepening the specific capabilities required to explore new opportunities offered “**on the side**” of the stage of the value chain where the firm is currently engaged (ibid, 49).

This is why Lema et al. (2018) points out that in the GVC approach the empirical investigation of ‘learning’ is often absent (Lema et al., 2018: 347). Indeed, it is the position of this paper that firm

business strategies such as *wage squeezing* or accounting maneuvers intended to temporarily pad bottom lines—rather than actual innovation efforts. In other words, we cannot delineate between upgrading resulting from innovation activities or upgrading resulting from a change in internal accounting methods.

innovation cannot be located in positional improvements along a GVC, but rather as a general capacity of the participating firm to operationalize learnings from GVC in local or other markets outside the GVC context entirely (off-chain). **Upgrading is a GVC-only term, that describes a favourable positional change of a participant firm within a GVC.** Innovation refers to that firm's general capacity to navigate the ever-evolving myriads of technological regimes with their various characteristics and benefits. This distinction is not merely semantic but greatly dominates our understanding of returns to specialization in GVC-based trade.

The following sections will elucidate this point. The argument, in brief, is that a source of murkiness surrounding the understanding and study of innovation in GVCs has to do with the focus on the *innovation outcomes*. The term upgrading, naturally and unavoidably, overlaps. The problem is that the 'outcome' is part of the innovation, but it is not the most useful unit of analysis. According to evolutionary economics, evolutionary economic geography, as well as new inroads within the GVC literature itself, the unit of analysis is the inherent 'capacity' of the firm to introduce changes. This definition of innovation (a) distinguishes itself from existing concepts such as upgrading and productivity, thereby offering new value to empirical analysis, (b) aligns with existing scholarship, and (c) captures a more 'modern' view of the *role* of innovation in firm specialization in trade. These points will be taken up in the following sections.

1.3 | Is Innovative a Capacity or an Outcome?

Evolutionary Economics frames technology as problem-solving knowledge, codified within "technological paradigms" (Dosi & Grazzi, 2006: 175). These paradigms establish heuristics, designs, and improvement trajectories, defining the evolution of techno-economic characteristics of artifacts and procedures. This conceptualization is pivotal for understanding innovation dynamics within Global Value Chains (GVCs), particularly concerning the smile curve phenomenon.

Technological trajectories exhibit cumulateness and locality. Knowledge evolves cumulatively from past experiences and locally from existing architectures. This structural understanding of technological knowledge and innovation patterns provides a foundation for discerning how firms navigate or shift between innovation pathways, a distinction critical for GVC analysis.

Economically useful knowledge is employed by business firms to do certain things—i.e. produce a car, refine a chemical, stitch a shirt, or find more efficient ways to build stronger bridges. This requires an application of "some collective pool of knowledge" to business in the form of routines of exploitation (production) or for exploration (research) (Dosi et al., 2008: 1165-1166). These routines, alongside other elements such as capital and specialized knowledge, are definitive components of firm 'capabilities', which, in turn forms part of our understanding of the observed heterogeneity in firm identity and economic performance given identical structural contexts. It is within this notion of 'capabilities' that evolutionary microeconomics investigate.

While the link between routines and capabilities can be convoluted due to the concepts' different usages in different literatures, one can think of firm 'capabilities' in terms of repeated organized activity, which, exists at a large-scale unit of analysis—i.e. it is "expressed in terms of the [...] outcomes it is supposed to enable" (Dosi et al., 2008: 1166). Routines are the building blocks of capabilities. They range in size from small and mundane to complex decision-making protocols and organizational practices that can be intuitively or consciously affected towards economic coordination ends, but also as "control and governance devices" (Dosi et al., 2008: 1167).

Routines can also be seen as an emergent phenomenon in business firms: while they do draw from the skills of individual workers within a firm, they represent more than the sum of those skills. Skills are among the building blocks of routines (proficiency in PowerPoint can certainly enable one to participate in an organizational practice that involves communication through presentation). What's more, 'skills' does not only refer to "knowing the job," but they are also "relational" and "organization-specific" bodies of knowledge (Nelson and Winter, 1982).⁶

This framework is used comparatively to delineate differences between business firms in terms of their 'capabilities', denoting their relative competitive strengths. Excellence in a particular capability means applying known knowledge well but also learning new knowledge. In other words, it is a balancing act "between continuity and change [done] in a competitively effective fashion" (Dosi et al., 2008: 1168). Seen in these terms, the concept is used to explain, for example, why in some instances incumbent industry leaders decline during a 'paradigm' change and at other instances they thrive, while at others yet survive but are overtaken in dominance by a new entrant (Dosi et al., 2008: 1175).

In this context, a significant conceptual clarity arises concerning the localization and nature of innovation:

Innovation as a capacity refers to the endogenous innovative propensity of firms. Their participation in GVCs may facilitate access to learning opportunities, especially given the support of the lead firm and through organizational and operational enhancements driven by regulatory and export-quality compliance. However, such enhancements must become endogenized routines in business firms to say they affected those firms' innovation capacities. Routines imply repetition until maturity—i.e. until they become competitively effective and allow the owner-firm access to new 'organizational practices'. Such was the case demonstrated by Pusaka Elektrindo and Harapan Elektrindo in adapting lessons learned on chain to solving a persistent local problem (off-chain), demonstrating the internalization of the building blocks of the on-chain training by MNEs. The internalization of the source skills and lessons and their deployment in an external context reflects entrenched capacity enhancement.

Innovative outcome refers to a discrete event, resulting from the firm's capacity or elsewhere, such as a one-off market opportunity, non-transferable improvements identified and directly administered by the lead firm to enhance chain efficiency, temporary labor rotations, or any host of other reasons. It may also reflect a change in management or a changing attitude towards risk, which are all important considerations in the building blocks of routines and skills that make up capacity; however, they do not perfectly correlate with the capacity itself⁷ and may not translate to it.

According to the World Bank in 2016 (the year the empirical data observed in this dissertation ends), innovation is currently, and has always been, pegged to an 'input-output' relationship in economics. In a World Bank Group (WBG) manual on firm level innovation studies, the authors identified that modern datasets dealing with innovation in economics should much more deliberately delineate between "**innovation assets**" (in traditional economics, an input) and "**innovation outcomes**," which may or may not derive from the innovation asset (WBG, 2016). What exists in the data is more heavily weighted towards outcome. Instead, the authors of this manual, and other scholars (see next section) propose a conceptual and empirical shift away from

⁶ Missing from the discussion is the concept of 'competency' as it is not central to the present study and would require somewhat of a dedicated treated due to its relative murkiness.

⁷ It is important to note that the general criticisms concerning innovation in this paper are not inherent or exclusive to GVC scholarship. Rather, they are widespread in many econometric studies across many topics, of which GVC is but 1 example.

the input-output framework and towards a treatment of innovation as assets—specifically, knowledge capital assets.

It is argued that the move away from innovation ‘outcome’ is a step in the right direction, but the move towards ‘innovation’ asset opens a series of complications in Capital Theory. These are addressed directly in [section 1.5.2](#), which helps to show that assets, in economics, must have certain attributes that innovation, a capacity, does not have.

The reality is that innovation functions as a capacity that both influences and is influenced by a firm's GVC positioning. While an innovation outcome is intrinsically linked to the innovative capacity that enabled it, it is not solely determined by it. As the coming chapters will show, many instances of ‘upgrading’ and innovation outcomes do not reflect an underlying capacity, such as for example, as Chapter 4 will show in terms of the functional ‘upgrading’ or Spanish and French industries in Supplier Dominated (SD) industries.

The understanding of innovation as a capacity instead of an outcome precisely aligns with Morrison et al. (2008)'s concept of exploring opportunities ‘on the side’ (off chain). This demonstrates a direct influence of GVC participation on capacity development. Within the same country and system, new products are developed to address the specific needs of the local market, independent of the lead firm, and **entirely outside the context of the GVC-related trade** that spurred the knowledge gain in the first place. This is distinct from ‘upgrading’—even as they happen concurrently—and it is also distinct from productivity enhancements or changes in the overall technological regime. As these constraints hold constant, and an existing firm resolves an existing problem in a local market, we can say there has been an increase in the capacities ‘of that firm to innovate, which would not be the same as saying that given a favorable positional change directed and led by a lead firm in a GVC to improve its supply chain. In the former, the onus of change is on the firm; while in the latter it ‘could’ arise from firm efforts, but could also arise from other sources.

The debate is not about the superiority of either the capacity-based or outcome-based approach to innovation. Rather, it highlights that one approach offers marginal utility, while the other exacerbates existing confusion. The advantages of a capacity-based definition of innovation, particularly within GVCs, and conversely, the disadvantages of an outcome-based definition, become clearer when considering that firm-level innovation does not occur in isolation. It is influenced locally by the NSI and globally by GVC governance, and more broadly by technological regimes.

1.3.1 | Innovation: Capacity Under Constraint

The imperative to comprehend innovation capacity is intrinsically linked to the concept of constraints. Firms operating within any market are invariably confronted with both opportunities and inherent ‘lock-ins.’ These lock-ins must be contextualized against the broader frameworks of technological regimes, Global Value Chain (GVC) governance, and National Systems of Innovation (NSI). These frameworks represent the institutional and conceptual structures developed by economists to elucidate the collective constraints impinging upon a firm’s innovative capacity—defined as its ability to navigate evolving paradigms through sustained efforts to adapt new techno-economic knowledge, manifested in routines and heuristics.

This section will systematically explore these topics, examining what a capacity-based definition of innovation reveals about GVC-participating firms’ ability to extract enduring knowledge from GVC engagement. It will also address how this knowledge should be measured, what the term ‘innovation’ should encompass within the GVC context, and

what it should exclude. Chapter 3 will build upon this discussion, forming the theoretical foundation for a dataset designed to empirically investigate how functional specialization influences innovative capacity at the industry level across Spain, Italy, France, Holland, and Germany.

1.3.1.1 | Technological Constraints

Rip and Kemp (1997) speak of technological *regimes*, a concept first elaborated by the authors, individually, in Kemp et al., (1994) and Rip (1995). “Regimes are outcomes of earlier changes,” they explain, “and they structure subsequent change. Novelty evolves within existing regimes and sociotechnical landscapes, starting at the micro-level of local practices” (Rip and Kemp, 1997, 338). Examples include the motorcar regime, factory-based production, or, at a presumptive point in the future, the hydrocarbon regime (Rip and Kemp, 1997). The technology associated with the motorcar, for example, is not the whole innovation. The motorcar is the artifact, a component of a larger whole that also includes steel, plastic, concrete, roads, and sociotechnical habits surrounding, and learned through, this technological regime.

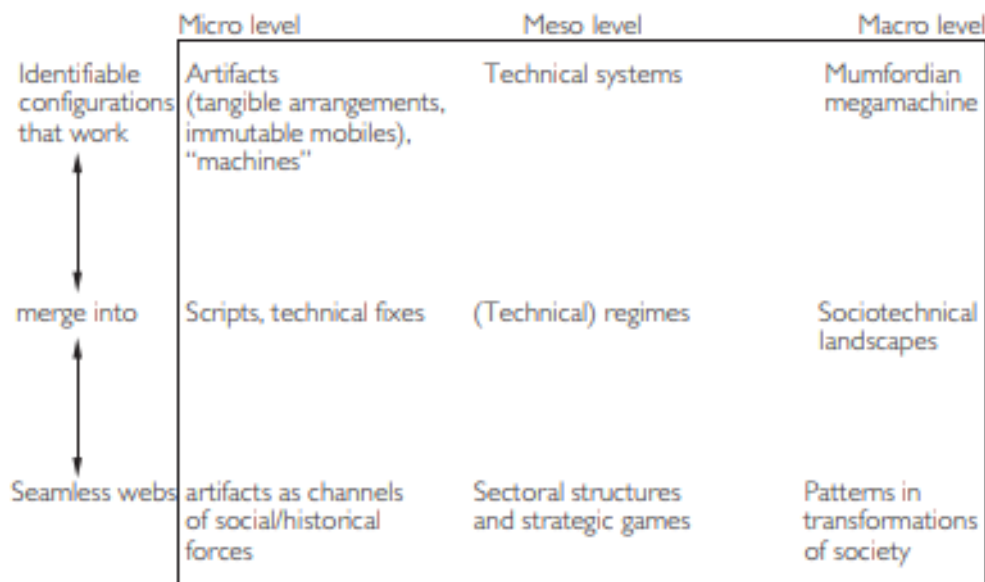
They introduce 3 important and interrelated concepts to this notion of technology: irreversibility, path-dependency, and lock-ins. The general theory describes the outcome of the repeated interaction between society, economy, and technology at the meso- and micro- levels as yielding sociotechnical landscapes with cultural and cultural-economic habits that are not easily reversible at the macro level:

Path dependencies refer to the interrelatedness of artifacts with other artifacts, infrastructure, and routines. New artifacts have to change or even undo these linkages, and this will meet with resistance. If governments or societies desire a new technology, they must not only construct its artifacts but also create a transition path toward it (Rip and Kemp, 1997: 354).

The resulting economic context is one where paradigms are **locked-in** until, indeed, an exit is drawn, either deliberately or through uncoordinated market forces (in economic terms, endogenously or exogenously). The conceptual framework of ‘technological regimes’ is suited for exploring, for example, why some knowledge may not mature into a paradigm, despite a theoretical advantage over the dominant regime or the question of how to increase likelihoods of better path dependencies or to identify and realize transitions from less to more desirable situations (Rip and Kemp, 1997: 371).

Rip and Kemp (1997) illustrates the proposed conceptualization of technology in an aptly titled figure:

Figure 2. “The Multilayered Backdrop of Novelty and Irreversibility”



Source: Rip and Kemp (1997: 339)

All levels play a role in reversibility and lock-in, determining and describing the path of economically useful knowledge and associated social forces. The horizontal axis is read as an ‘increase of scope.’ The entrenchment of technology increases, and with it the habits engrained in the socioeconomic forces that make up its environment, going from micro to macro level. “Down the vertical axis, the configurations become more heterogeneous and reflect the seamless-web character of technological change” (Rip and Kemp, 1997: 340). A timely example concerns Artificial Intelligence technology’s tenuous impact on labor-capital economics, and therefore, social dynamics. The technology is expected to pose an employment dilemma to disrupt sectoral structures and lead to a wide range of strategic games, as have previous technological regime developments since 1841.

Based on this analysis, it is posited that innovation, particularly within GVCs, should be defined as occurring ‘on the side.’ This conceptualization is crucial for disentangling innovation from the often-conflated notion of ‘upgrading.’ While upgrading typically refers to improvements in a firm’s position within a GVC—such as moving from assembly to manufacturing, or from manufacturing to design—it does not inherently signify a fundamental shift in the firm’s underlying innovative capacity. Upgrading can be a consequence of external pressures or lead firm directives, rather than the endogenous development of new problem-solving capabilities. This distinction is vital for a more precise analytical framework, preventing the oversimplification of complex GVC dynamics and avoiding teleological interpretations where all GVC participation automatically leads to genuine innovation.

Innovation capacity is not merely the passive receipt of knowledge transfer but an active agency in adapting, reconfiguring, and creating new knowledge that allows a firm to respond to evolving techno-economic challenges. This dynamic interplay means that a firm’s innovative capacity is both profoundly affected by its GVC participation and, in turn, influences its ability to extract lasting gains and navigate the constraints imposed by technological regimes. This understanding will motivate our empirical approach in Chapter 3.

1.3.1.2| Innovation Ecosystems: Institutional Enablers and Constraints

As a humanistic concept, innovation is not new. It has persisted in man's imagination since time immemorial. As a codified scholarly concept, however, it is relatively novel, going back to 20th century theories such as Joseph Schumpeter's theory of the firm and creative destruction. Schumpeter revolutionized the field because he was the first to build a systematic, rigorous framework explaining *how* and *why* firms innovate. He institutionalized the concept in three specific ways: he separated 'invention' from 'innovation', clarifying that an invention is a scientist's breakthrough, but *innovation* is an economic act requiring a firm to commercialize it. He integrated the firm and entrepreneur into economic theory: He made the firm's strategic choices the centerpiece of economic growth and proved that firms do not just compete on price (making an existing widget a penny cheaper); they compete by destroying each other's markets with completely new paradigms. He created the first innovation typology: his "Five Forms of Innovation" (new products, processes, markets, supplies, and organizations) provided the first structured taxonomy that scholars could use to study and measure business strategy. Others noticed technological change before him, but Schumpeter wrote the "conceptual edifice" that scholars still use today to study active, firm-level innovation (Schumpeter, 1934; 1943).

Fagerberg and Sapprasert (2011) catalogued every annual addition to the Web of Science based on whether scholarly publications include the word, "innovation," in the title. In the 1960s and before, little, if any, attention was given to innovation as a stand-alone concept or analytical framework (Fagerberg and Sapprasert, 2011: 669). In the 3 decades after, the number of publication titles featuring the word increased steadily, eventually quadrupling by 1990. In 1990, the linear increase broke upwards exponentially, doubling in just 1 decade (Ibid, 670).

The trend break is attributed to a reframing from firm-level theories and data to the concept of National Systems of Innovation (NSI). NSI is a concept, but also a framework. It shares with our previous understanding of innovation the notion of "interactive learning" as the core activity contained therein. As a framework, NSI seeks to explain, comparatively, how nations produce knowledge and learning mechanisms through interconnected networks of norms, actions, institutions, and actors that act upon business firms and technological education. As a concept, it is a knowledge processing system that "is constituted by a number of elements and by the relationship between these elements [...] that interact in the production, diffusion and use of new and economically useful knowledge [...] encompass[ed] inside the borders of a nation" (Lundvall, 1992: 86). This literature was initially developed by 3 scholars and their contributions: Bengt-Ake Lundvall (1992), Christopher Freeman (1995), and Richard Nelson (1993). These works largely remain in 2025 the *bible* for innovation studies.

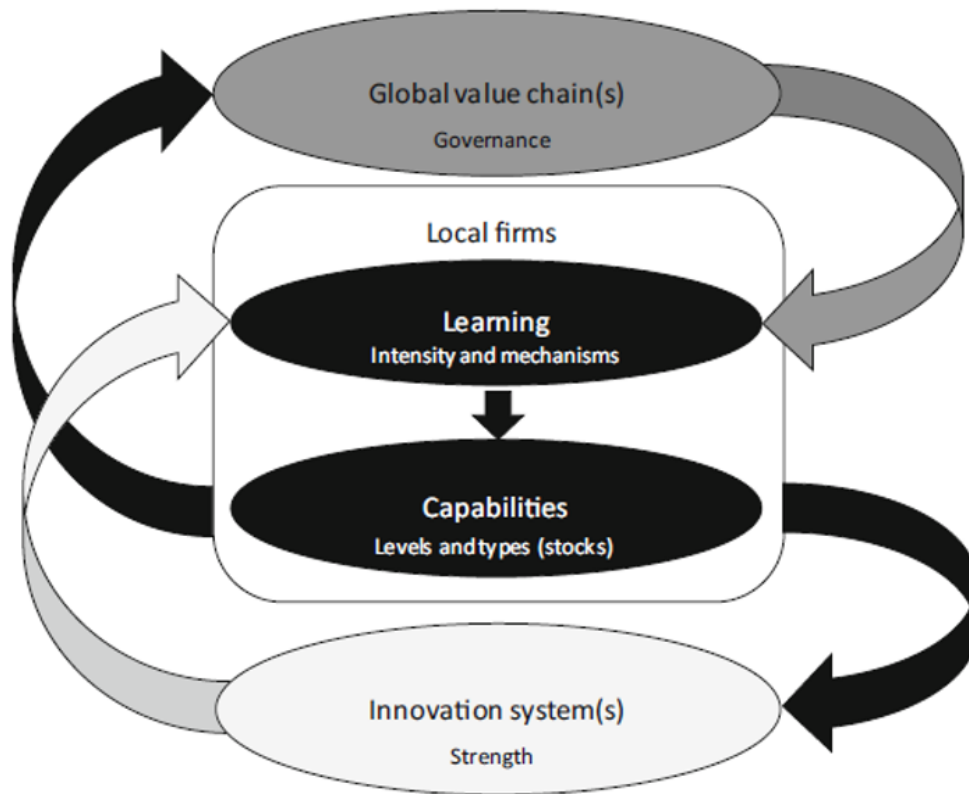
Conceptually, national systems of innovation can encompass *anything* that affects learning and knowledge application for solving socio-economic problems. Common factors for consideration include, according to Nelson's seminal 1993 contribution on the matter, "the allocation of R&D activity and the sources of its funding, the characteristics of firms and the important industries, the role of universities, and government policies expressly aimed to spur and mold industrial innovation" (Nelson, 1993: 19). It is here that we can find some common indicators of technical capability (and, therefore, points of comparison) between different NSIs. Again, while conceptually infinite, standard measures include the likes of engineering students as percentage of total population, R&D as a percentage of GNP, industry R&D as a percentage of total, robots per million in employment (though this one may be continuous), and percentage group in third level education or higher (Freeman, 1995: 10). While somewhat challenged under the guise of **globalization**, the concept of NSI remains a dominant paradigm in the business of *learning how we learn*.

According to Nelson, after compiling three decades of work on innovation and NSI, “there are certain matters we are sure about” (Nelson, 20):

One is that [...] the efforts of governments and universities may support, but cannot be a substitute for the technological efforts of firms. Another is the importance of a nation’s education and training systems. A third is that a nation’s fiscal, monetary and trade policies must spur, even compel, national firms to compete on world markets (Nelson, 20).

Even this concise description of the NSI literature underscores that novelty and change never occur in a vacuum. Instead, the economic capacity for change is significantly determined by what national institutions permit, enable, or exclude. In the context of developing nations, for which the GVC literature serves as a development framework, this point must also extend to include active hindrance and security concerns (e.g. data regulations in some nations that restrict certain economic advancements related to big data).

Figure 3. “GVC-IS Co-Evolution and Firms’ Innovative Processes”



(Source: Lema et al. (2018:353; original chart title)

The primary argument of the paper from which figure 3 and its title are derived is that national innovation ecosystems, with what that entails in terms of institutions, norms, and infrastructure, **evolve alongside GVC innovation systems**. In other words, the local and the global co-evolve and are an indispensable part of each other’s theoretical frameworks. The figure emphasizes these connections, depicting ‘learning’ and ‘capabilities’ as the units of analysis at the firm level. The strength of the NSI (the local) and the governance modality of the GVC (the global) determine the available mechanisms of **learning** and the intensity of the knowledge gained and adapted.

Knowledge learned and repeated becomes capabilities, which reinforce both the NSI and the GVC.

To recall the example of Indonesian firm upgrading in Japanese GVCs in the context of figure 2: the arrow indicating the entrenchment of learned knowledge into capabilities is affected by both the governance mode of the GVC and the local Indonesian NSI (including the relevant subnational innovation systems). The fact of enhanced productivity within the GVC owed to learnings from that GVC is an instance of upgrading; the fact of developing custom-made antennas for the Indonesian market without any changes to the institutional or technological regimes facing the developers indicates an entrenchment of lessons into capabilities (given the constraints the previously prevented that innovation remained in place).

1.3.2| Learning in GVCs

Perhaps to contextualize the above discussion in more concrete terms, some stylized examples are in order. Specifically, examples of firm level learning in GVCs, structured by the learning mechanism itself: what according to the above scholars, is only ever “mentioned at best.” Following from figure 2, learning in global value chains comes in many forms and with varying degrees of intensity, both dimensions affected by firm capabilities, which also affects the entrenchment of knowledge into routines and heuristics (recall the cumulativeness and locality of technology). Table 1, below, breaks down some important learning mechanisms documented in the GVC literature. **Each mechanism is defined and marked as either ‘top-down’ or ‘bottom-up’.** This is this author’s own interpretation of these mechanisms and is an attempt to underline the degree to which each particular learning mechanism requires the involvement, and perhaps more importantly, the initiative of the lead firm (or big buyers) within a GVC. This element is important given the documented prevalence of ‘strategic hinderance’ of access knowledge and functional upgrading, and the active intellectual monopoly capitalism documented in the literature and discussed in the previous section.

Table 1. Select Learning Mechanisms in Global Value Chains⁸

(blue = bottom-up learning; red = top-down; black = both)

⁸ Many of the surveyed learning mechanisms were highlighted in de Marchi et al. (2017), so much so that their framework could have been directly transplanted into this work were it not for the fact that they focus exclusively on GVC learning mechanisms in LDCs. As such, a variety of differences exist between this set of learning channels and those considered by de Marchi et al. (2017). Nonetheless, their review was seminal in connecting the present study (and others) to the appropriate articles and bodies of literature.

Learning Channel	Definition	Documented in
Imitation	Companies may observe and replicate the successful strategies of their competitors or partners in the value chain	Korea's technology sectors 1980-2000 (Kim, 1997); electronics GVC in Indonesia (Kadariusman, 2012)
Technology Spillovers (very often observed to be FDI-induced, & mostly greenfield FDI)	Knowledge and technology can spill over from one firm to another within a value chain, leading to learning and innovation	Estonian manufacturing firms (Meyer & Sinani, 2002); Uruguayan manufacturing receiving FDI (Kokko et al., 1996); mining, agribusiness, and apparel in sub-Saharan Africa (Farole & Winkler, 2014)
Mutual Face-to-Face Learning Interactions	Interactions between employees of different firms in the value chain can lead to the exchange of ideas and knowledge (typically informal process)	Altenburg (2006) provides a thorough overview
Inter-firm Collaboration	Companies may work together on formal joint projects or initiatives, leading to shared learning and innovation	Coffee 'genetics research' joint venture led by IllyCafe (Cafaggi et al., 2012)
Training Organized by Lead Firm	Lead firms frequently organize formal training for their suppliers' employees for reasons of product quality, compliance, or cost.	learning from managers of subsidiaries operating in Indonesia (Kadariusman, 2012); similar mechanisms observed in Mexico (Sturgeon & Kawakami, 2011)
Direct Tech Transfer	Firms may acquire new technologies or knowledge through licensing agreements, joint ventures, or mergers and acquisitions	Developing country reliance on direct transfer (Fagerberg et al., 2010); Colombian suppliers of chili pepper paste receiving technical assistance from lead firm, Tabasco (Melendez & Uribe, 2012); Brazil's Sinos Valley footwear cluster (Schmitz, 2006)

Supplier-Buyer Relationships	Companies may learn from their suppliers or customers through interactions and feedback, commonly forming learning <i>dyads</i>	Italy's motorcycle industry in the 2000s (Ferriani et al., 2014); wind energy industry in China (Lema et al., 2013)
Industry Associations & Networks	Participation in industry associations or networks can facilitate learning and knowledge sharing among firms in a value chain (like supplier-buyer relationships but featuring large networks instead of learning pairs)	Italy's motorcycle industry in the 2000s (Ferriani et al., 2014)
Reverse Engineering (RE) ⁹	Companies may acquire and analyze products or technologies developed by competitors or partners to understand how they work and develop their own versions	Most associated with the automotive industries of China and India (Altenburg et al., 2008)
Employee Mobility (skilled workers and managers)	Employees moving between firms within the same GVC can bring knowledge and expertise with them, leading to learning and innovation in their new workplace	Skilled labor mobility in Ghana (Fu et al., 2014); indonesia's electronic exports (Kadariusman, 2012)
Compliance	Lead firm instructs the adoption and adherence to specified international or regional product and process standards. This <u>may or may</u> be coupled with direct technology transfer and/or technical assistance	Found to be a common learning mechanism in the production of electronics (Sturgeon and Kawakami, 2011; Kadariusman, 2012), specifically mobile phones (Brandt & Thun, 2011), as well as the export of agricultural products, most commonly those intended for EU markets Padilla-Perez, 2014)

⁹ Please note that, as a firm learning mechanism, 'reverse engineering' commonly falls under the wider umbrella term of 'imitation'. See de Marchi et al (2017) for a more thorough discussion of the convergence and divergence of the two terms.

Learning mechanisms such as those defined above, as highlighted by Lema et al. (2018) and depicted in Figure 2 (“learning”), are distinct from, yet intricately related to, a firm’s innovation capacity. While these mechanisms may influence and be influenced by capacity, they do not constitute innovation capacity itself. Rather, they are manifestations or facilitators of it.

This distinction is paramount, particularly for empirical investigations, including the present study, which seek to substantiate arguments such as the central thesis of this work: that GVC participation affects innovation distinctly depending on the function performed by the participating firm. To rigorously address this, this chapter posits that innovation is fundamentally a capacity, which when measured as an outcome creates the observed problems. This definition, as demonstrated, offers superior analytical utility by aligning more closely with existing literature and by deliberately differentiating itself from established, yet often conflated, terms such as ‘upgrading.’

Existing measures of innovation, such as patents, other intellectual property rights, or R&D expenditure, often serve as proxies for innovative outcomes. While valuable, these metrics may not fully capture the enduring propensity to innovate. A more robust empirical approach would involve defining and measuring this propensity over time, comparatively across similar firms, and aggregated to industry or national levels. Surveys like the Community Innovation Survey (CIS), which collect firm-level data on the introduction of product, process, and other innovations, offer a promising avenue. By aggregating these binary (yes/no) responses, a by-industry or by-nation propensity score can be constructed, accurately reflecting a group of firms’ ability to introduce novelty into their economic activities. For this reason, previous studies have utilized CIS data, aggregated at the industry level (see Coveri & Pianta, 2022 and Reljic et al., 2023).

Such propensity scores can then be juxtaposed against GVC participation data to empirically ascertain whether participation genuinely leads to an increase in innovation capacity over time and across geographies, without necessitating assumptions of heterogeneity between firms, industries, or nations. Furthermore, as indicated in Table 1, many learning opportunities within GVCs are inherently collective and relational, occurring through group interactions. As the subsequent chapter will elaborate, this characteristic aligns with the understanding of learning as ‘cumulative’ and ‘local,’ and, as translated by evolutionary economic geography scholars, as ‘relational’—implying that the acquisition of knowledge by one firm within a cluster often facilitates its diffusion to others. This underscores the systemic nature of innovation capacity development.

Building upon this foundational understanding, the forthcoming Chapter 2 will introduce the resulting data strategy and provide summary statistics, while Chapters 3 and 4 will analyze this data to present the empirical findings, culminating in the overarching conclusions of this study in Chapter 5.

1.4| The Role of Governance in GVCs

1.4.1| GVC Governance and Innovation

The 2005 work by Gereffi, Humphrey, and Sturgeon established a theoretical framework that identified five distinct types of global value chain governance: **hierarchy, captive, relational, modular, and market** arrangements. This typology represented a significant advance over earlier binary distinctions between market and hierarchy, providing a more nuanced understanding of the spectrum of coordination mechanisms that characterize global production systems.

The theoretical framework was built upon three key determinants of value chain governance patterns:

- (1) the complexity of information and knowledge transfer required to sustain particular transactions;
- (2) the extent to which this information and knowledge can be codified and transmitted efficiently; and
- (3) the capabilities of actual and potential suppliers in relation to transaction requirements.

It is immediately apparent that the third determinant of governance concerns the capabilities of firm participating in relation to the transaction requirements, which are themselves the first two determinants. As such, the governance modalities available to govern a GVC arrangement between lead and supply firms is strongly defined by firm capacities. For example, Captive value chains represented an important governance type, characterized by small suppliers being transactionally dependent on much larger buyers. In these networks, suppliers face significant switching costs and are therefore "captive," with arrangements frequently characterized by high degrees of monitoring and control by lead firms. This governance pattern proved particularly relevant for understanding the position of developing country producers in global production systems.

These three variables, when combined in different configurations, generate distinct governance patterns that range from low to high levels of explicit coordination and power asymmetry—namely, the 5 governance ‘arrangements’ listed above. Captive value chains, for example, are characterized by small suppliers’ transactional dependence on larger buyers. Within these networks, suppliers encounter considerable switching costs, making them “captive” and subject to extensive monitoring and control by lead firms. This governance pattern is especially pertinent for comprehending the position of developing country producers in global production systems.

Returning to the Indonesian example, the pivotal role of the innovative capacity of local firms participating in Japanese GVCs becomes evident. Had their capabilities relative to transaction requirements been unfavorable, the outcome of ‘participation’ could have been entirely different. Instead of fostering learning, developing new capacities, and establishing flexible and efficient production systems, these firms might have faced lock-ins under a captive or hierarchical GVC governance modality. A common misconception and oversimplification in the literature is that the governance scheme is a ‘choice’ made by the lead firm. In reality, as Gereffi, Humphrey, and Sturgeon (2005) demonstrated, it is determined by the innovation capacity of participating firms in relation to key transaction characteristics.

This distinction is critical because the localization and measurement of innovation have profound implications for two significant concepts: functional upgrading and Intellectual Monopoly Capitalism (IMC).

The evolution of GVC governance theory has placed considerable emphasis on understanding how different governance patterns influence upgrading opportunities for firms, particularly those in developing countries. Research indicates that distinct governance patterns create varied upgrading trajectories and constraints. Insertion into quasi-hierarchical chains, for instance, has been shown to offer highly favorable conditions for rapid process and product upgrading but simultaneously impede functional upgrading. This finding challenges earlier optimistic assumptions regarding the automatic progression of developing country producers up value chains, revealing instead that power relationships within chains can erect barriers to certain types of upgrading. Similarly, lead firms in captive chains (and, to a lesser extent, modular chains) have been observed to strategically hinder the functional upgrading prospects of their suppliers.

1.4.2| Multi-Scalar Governance: The Role of the Participant in Learning

The intensification of intangible asset deployment as economically useful technologies within global value chains (GVCs) has fundamentally reshaped the capture and distribution of *gains*, leading to the emergence of what Pagano (2014) calls "intellectual monopoly capitalism" (IMC). In this context, strategic control over intangibles—encompassing elements such as intellectual property, brands, technical standards, organizational know-how, and data—produces persistent market power and monopolistic rents, especially via legal protections, network externalities, and scale economies. This evolving regime reinforces and steepens the 'smile curve', whereby value creation and appropriation disproportionately accrue to actors operating in intangible-intensive upstream and downstream segments (R&D, design, marketing), and away from fabrication and assembly sectors characterized by global competition and margin compression (Durand & Milberg, 2020). As a result, GVCs are marked by pronounced asymmetries in 'value capture', with economic geographies either consolidating control over high-value nodes or being relegated to tangible-intensive, low-rent activities.¹⁰ To understand, specifically, how this works, one ought to turn to recent advances in the GVC governance and Evolutionary Economic Geography (EEG) literatures.

Recent studies suggest that governance of global value chains (GVCs) is fundamentally dynamic, marked by continual evolution as firms and industries adapt to changing transactional complexities, codification potentials, and supplier competence. More recent (2010+) Theoretical advancements highlight that governance structures—whether hierarchical, market-based, captive, or relational—are not fixed, but rather recalibrated in response to both endogenous capability development and exogenous market or regulatory pressures (Gibbon et al., 2008; Dallas et al., 2019a). Case studies from sectors such as bicycles (see, for example, Benson-Rea et al., 2023) and apparel (Andreoni and Boys, 2023) exemplify these trajectories: hierarchical or captive arrangements often give way to more modular or relational forms as suppliers acquire specialized capabilities, industry standards proliferate, and the need for intensive oversight diminishes.

This dynamism is further accentuated by the interplay of internal chain dynamics and external institutional forces. Regulatory shifts, technological advancements, and the strategic imperatives of

¹⁰ The conceptual connection of Pagano's intellectual monopoly capitalism as the theoretical foundation belying the relationship between specialization and value capture was first suggested by Coveri and Zanfei (2022).

lead firms or buyers catalyze transformations in governance modalities. For example, the imposition of private standards by European supermarkets in the fresh produce sector led to more explicit, formalized coordination mechanisms (Martinez and Poole, 2004) in supply chain.

Recent GVC scholarship has moved beyond earlier interpretations cantered exclusively on lead-firm dominance, emphasizing instead the polycentric and multi-scalar nature of governance in GVCs. In this perspective, governance is not simply exercised by lead firms over entire value chains, but emerges through multiple actors, relationships, and institutional arrangements operating across different levels.

Building on this view, Dallas, Ponte, and Sturgeon propose a framework aimed at explaining how specific linkages within value chains are governed, rather than governance at the level of the whole chain (Dallas et al., 2019: 124). **They distinguish between governance as driving, linking, and normalizing, and identify four forms of power in GVCs—bargaining, demonstrative, institutional, and constitutive—depending on whether power is exercised through dyadic or collective arenas, and through direct or diffuse mechanisms.** This broader governance perspective helps explain why learning and innovation opportunities differ substantially across firms and GVC functions.

This demonstrates the departure away from the notion of whole chain governance. While governance “typologies” remain relevant, it is argued in this work that they are relevant as their determinants (see above) are based on the functional profiles of firms, which forms the basis of governance theory whether that theory is based on dyadic/collective ‘linkages’ or whole chain governance. While the notion of ‘function’ is seen in the founding of GVC governance theory, it is only now explicitly becoming the focal lens for analysis due to the recent abundance of data for such an analysis. The important point to note here is that there is an ongoing move away from whole chain governance in favor of specific linkages all whilst maintaining the important of the complementarity between supplier and buyer functions/capabilities that form the original basis of GVC governance theory.

The evolution of GVC governance theory placed significant emphasis on understanding how different governance patterns affect upgrading opportunities for firms, particularly those in developing countries. Research revealed that different governance patterns create distinct upgrading trajectories and constraints. **Insertion in quasi-hierarchical chains (or later better conceived off as quasi-hierarchical linkages or dyadic, direct-power linkages) was found to offer very favorable conditions for fast process and product upgrading but to hinder functional upgrading.** This finding challenged earlier optimistic assumptions about the automatic progression of developing country producers up value chains, revealing instead that power relationships within chains could create barriers to certain types of upgrading. Similarly, lead firms of captive chains (again, or captive linkages) were found to strategically hinder the functional upgrading prospects of suppliers.

This ‘strategic hindrance’ is done to safeguard the core competency of the lead firm or the firm exerting the asymmetric power, which has a vested interest in maintaining a monopoly on the tacit knowledge related to intangible functions while relegating the more codified, explicit functions to their suppliers. This form of knowledge control is sometimes described as Intellectual Monopoly Capitalism. By mapping who performs and governs each function, researchers can pinpoint where power lies; for example, lead firms may govern high-value functions like design and branding through explicit standards or proprietary knowledge, while outsourcing lower-value production tasks under looser governance regimes. This granularity reveals how governance structures are not uniform across the chain but can differ sharply by function, further conforming to the ‘piecemeal’ reality of GVC trade marked with varied power operations within one chain.

This dynamic reframes the central analytical question: rather than simply asking whether a lead firm will guard its core competencies and how, it is more fruitful to interrogate the specific circumstances under which such protection becomes a certainty, and to investigate the moderating forces influencing both the durability and efficacy of knowledge monopolization strategies, and the prospects for suppliers to circumvent vertical barriers to learning. To that end, the innovation capacity of the GVC-participating firm plays a critical role—perhaps the key role—in determining its relationships, vertically and horizontally, and interactions within GVCs, including the degree to which ‘guarded’ knowledge can be gained and utilized. In the same manner, the very capacity of strategically guarding knowledge requires a strong innovation capacity, specifically as concerns IKAs.

The central implication is this: while the Smile Curve hypothesis suggests that value capture is unevenly distributed across functions—with intangible-intensive activities such as design and logistics commanding disproportionately higher returns—this structural reality does not operate in isolation.

As GVC governance is increasingly understood as multi-scalar, unfolding at the level of specific linkages rather than entire chains, access to these high-value opportunities is less mechanically determined by the lead firm or large buyers and more contingent on firm-level capabilities. In this evolving landscape, participation alone no longer guarantees upgrading prospects (if it ever had); instead, firms are progressively expected to cultivate the absorptive capacity, strategic intent, and innovation capabilities required to navigate, negotiate, and, where possible, reshape their roles within GVCs. In other words, while governance structures continue to condition opportunities, the burden of leveraging—or even creating—those opportunities is increasingly shifting toward the firm itself, albeit unevenly and within the constraints imposed by asymmetric power relations.

1.5. The Role of Intangible Assets in GVCs

As discussed in [section 1.1](#), contemporary GVCs are increasingly characterized by pronounced asymmetries in value creation and capture, with intangible-intensive upstream and downstream activities typically generating greater returns than fabrication and assembly. The smile curve hypothesis, together with emerging evidence on the growing role of intangible assets in global production, suggests that participation in GVCs alone is insufficient to explain heterogeneous development and innovation capacities. Rather, the specific functions performed within GVCs—and their associated intangible content—appear to be crucial.

Having clarified the distinction between innovation, upgrading, and technological change, this section revisits the role of intangibles in GVCs more systematically. **In particular, it examines how intangible assets shape governance asymmetries, learning opportunities, and firms' capacity to accumulate capabilities, ultimately motivating a functional perspective on GVC participation and innovation.** The following sections therefore unpack the rise of the intangible economy, the role of Intangible Knowledge Assets (IKAs), and the relationship between economic functions, specialization, and innovation in contemporary GVCs.

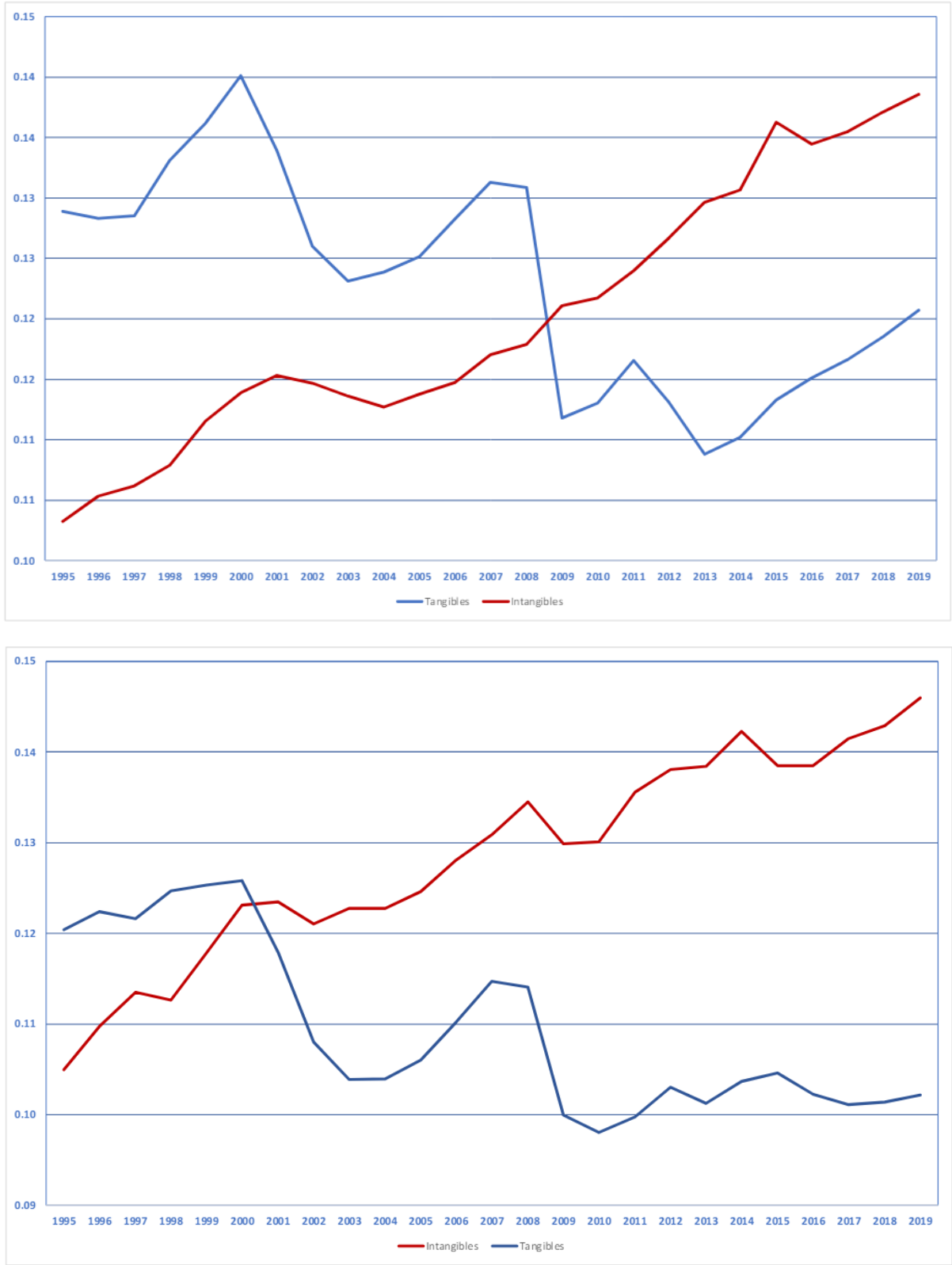
1.5.1 | Intangible Knowledge Assets (IKAs)

The growing importance of intangible assets has profoundly reshaped the organization of production, value creation, and innovation in contemporary economies. As shown in Figure 4, the contribution of intangible assets to Gross Value Added in both the EU and the United States has progressively overtaken that of tangible assets, with this transition occurring earlier in the United States and somewhat later in Europe. This transformation provides an important backdrop for understanding the increasing scholarly emphasis on intangibles, knowledge-based competition, and functional specialization in GVCs.

The distinction between tangible and intangible assets is analytically important because the two differ substantially in their economic properties, accumulation processes, and implications for value capture and innovation. Tangible assets—such as machinery used in textile production—have observable prices, are geographically fixed, and depreciate according to physical use and wear. Intangible assets, by contrast, are often non-rival, partially non-excludable, and difficult to measure directly. Organizational routines, proprietary designs, algorithms, patents, or production models can often be replicated, adapted, and deployed across locations at relatively low marginal cost, while simultaneously remaining strategically protected.

These differences matter for GVC analysis because the increasing importance of intangible assets helps explain why value creation and appropriation tend to concentrate in specific functions, particularly knowledge-intensive upstream and downstream activities. Understanding the nature of intangible assets is therefore essential for explaining heterogeneity in learning opportunities, innovation capacity, and upgrading trajectories across firms and industries participating in GVCs.

Figure 4. (In)tangible Share of GVA in the USA and the EU, 1995-2019



Source: (Bontadini et al., 2023: 20-21)

These differences between tangible and intangible assets also have important implications for how knowledge is distributed and controlled within GVCs. Lead firms often have strong incentives to strategically safeguard tacit knowledge related to intangible-intensive functions, while delegating more codified and standardized activities to suppliers. Such forms of strategic hindrance serve to preserve the core competencies of lead firms and limit the diffusion of knowledge underpinning high value-added activities.

This form of knowledge control is sometimes described as Intellectual Monopoly Capitalism (IMC), an economic system in which firms derive monopoly power primarily from intangible assets—such as intellectual property, data, algorithms, networks, and platforms—rather than from physical capital or economies of scale. Scholars such as Jonathan Haskel and Stian Westlake argue, in their book: *Capitalism Without Capital* (Haskel & Westlake, 2017) that intangible assets foster winner-takes-all dynamics due to their scalability, sunk costs, and complementarities. In turn, economists such as David Teece have emphasized how such dynamics may reinforce the concentration of market power, innovation, and profits among a limited number of “gatekeepers,” thereby potentially exacerbating inequality and weakening market dynamism (Teece, 2025).

Intellectual monopoly capitalism directly shapes GVC governance by amplifying power asymmetries. Lead firms (e.g. Apple, Unilever) leverage intangibles—proprietary standards, software, or certifications—to enforce quasi-hierarchical or captive control. For example:

- **IP and Standards:** Suppliers often face “captive” governance when lead firms impose codified IP and process standards, thereby obstructing functional upgrading (e.g. design, branding). This dynamic has been observed to lock Latin American clusters in traditional manufacturing into low-value assembly.
- **Data Dominance:** Platform firms (e.g. Amazon) exploit data monopolies to dictate terms, reducing suppliers to price-takers and stifling intersectoral upgrading.
- **Regulatory Capture:** Lead firms influence standards (e.g. ISO, sustainability certifications) to exclude smaller producers, reinforcing monopolies while externalizing risks (e.g. labor/environmental costs).

Thus, intangible assets enable lead firms to extract rents globally while simultaneously constraining cluster upgrading. This is evident in sectors such as electronics (modular chains) and agriculture (relational chains), where supplier capabilities are neutralized by IP dependencies. This nexus entrenches a “high-road” competitiveness for monopolies and a “low-road” trap for suppliers. More pertinently, it calls into question the purported gains from participation argued by various case studies of upgrading presented in the literature. **Since governance is partly determined by a firm’s own ‘capacities’ relative to new ‘transaction requirements,’ it follows that the innovative capacity of the firm, though impacted by GVC trade, is the dominant determinant of its gains from participation. This is because it enables the firm to extract gains despite active efforts by lead firms and large buyers to limit change and strategically guard core competencies from participants.**

1.5.2| (In)tangibles: A Problem of Symmetry and Equivalence

Carol Corrado, Carles Hulten, and Daniel Sichel are perhaps the most prolific co-authors when it comes to fitting intangibles into Capital Theory. Their 2005 work, often referred to as CHS (2005)—

including in the present work—is the basis of important calculations that spurred a renewed interest in intangible capitalization, finding \$800 billion USD missing from US national accounts (Corrado et al., 2005). The same authors, in 2006, explain that in terms of Capital Theory, and from the standpoint of consumption, there is obvious equivalence between tangible and intangible capital:

Capital theory implicitly defines capital in the context of an optimal consumption plan based on the maximization of an intertemporal utility function subject to the usual constraints [...] The solution to this optimization problem has an important implication for the treatment of intangible capital: any use of resources that reduces current consumption in order to increase it in the future qualifies as an investment. This result argues for symmetric treatment of all types of capital, so that, for example, spending on R&D and employee training should be placed on the same footing as spending on plant and equipment. Moreover, this symmetry principle requires that most business expenditures aimed at enhancing the value of a firm and improving its products, including human capital development as well as R&D, be accorded the same treatment as tangible capital in national accounting systems (Corrado et al, 2006: 9).

However, from the production standpoint, the issue of equivalence becomes more complicated::

Some have argued – particularly in the accounting world – that several characteristics of intangibles disqualify them from being counted as capital; namely, the lack of *verifiability* for intangible assets that are not acquired through market transactions; the lack of *visibility* of intangible assets after their acquisition that complicates efforts to track past vintages; the *non-rivalness* of some intangible assets; and the lack of *appropriability* of the returns from some intangibles (ibid, 10).

The authors argue that while important distinctions, these attributes of intangible assets are “no more relevant for the capitalization issue than are differences in the characteristics of equipment, structures, and land” (ibid). While that is the case, they are, however, highly relevant for locating intangible assets and their diffusion across systems of commerce, including global value chains. **Product-based classifications in GVC studies struggle to navigate this asymmetry between capital types.**

In the specific context of global value chains, the importance of intangibles knowledge in modern value chains is underscored by Chen, Los, and Timmer (2018), estimating that intangibles account for one third of the total value produced in all GVCs, a figure they show has been constantly rising since the turn of the century, as is the case with (in)tangible share of GDP (Chen et al., 2018) reported in the figure above. Given the rise of intangible assets and their asymmetry with tangibles assets, one begins to understand why the role and purpose of innovation in economic theories might begin to change.

While nascent conceptual and empirical works do investigate the relationship between GVC participation and intangibles, many of these studies examine asset stocks, not their sources, meaning little is known about the generation and diffusion of intangibles that arises in and because of GVC participation.¹¹ This is important, as Biondi and Reberlioux (2012) find that ‘how’ a firm acquires intangible assets contributes to defining the “firm-specific environment,” which is distinct to and not replicable by the market or the value chain to which it belongs (Biondi & Reberlioux, 2012: 283). For

¹¹ In fact, without R&D data, there would be almost no quantitative information about intangible assets worldwide before the development of EU Klems and Globalinto. This is precisely why this paper avoids discussing the role of R&D; it is not that it is unimportant, but rather that all present studies focus exclusively on it, and there is no need for elaboration in future studies (*ceteris paribus*) except to prolong data series.

example, the decision between ‘buying’ or ‘making’ an intangible asset not only determines the trajectory occupied by that asset but the innovative profile of the firm. This is yet another implication of the conceptual murkiness of the term innovation, which is simply exasperated in the case of intangibles.

There is symmetry between intangible and tangible assets that qualifies the former to be considered assets, but there is also dissymmetry based on their distinctive attributes, **which disqualifies both types of assets from relating to innovation in the same manner.** The lack of verifiability, appropriability, and visibility, coupled with the fact of non-rivalness have implications for the accounting of intangibles as stocks, but they also have implications for the diffusion of these types of assets in GVCs—i.e. the acquisition and generation processes themselves. It is also these precise qualities that allow for the monopolization of IKAs for rent extraction, giving rise to a new role for innovation to support the often-exclusive monetization of non rival, non-appropriable, and non-verifiable knowledge.

In product-based classification, gains from specialization arise from the efficacy (“labor and capital productivity”) with which inputs are transformed into outputs—it is the *slope* of proverbial production curve. These benefits are universal across trading partners (greatest number of products for the greatest number of participants per output level/ disposable budget). Changes in specializations arise from exogenous impetus for technical change that alters relative productivity of capital and labor across the economic participants, leading to a different optimal universal allocation of specializations. **In this understanding of specialization, innovations affect the rate with which *inputs* are transformed into outputs** given a particular technological regime, allowing improvement along the triple constraint of time, quality, and cost. This is as per the ‘comparative advantage’ theory in classical economics.

The traditional understanding of specialization within comparative advantage, which posits gains through cost reduction and output increase, is fundamentally incompatible with how economic value is extracted in modern Global Value Chains (GVCs). In function-based GVCs, specialization primarily involves the extraction of rent from knowledge assets, a mechanism distinct from classical notions of efficiency-driven trade. This shift transforms trade into a zero-sum game, inherently creating winners and losers, as monetization often relies on restricting access to intangible knowledge assets (IKAs) through patents, proprietary information, licensing, and royalty agreements.

Research consistently demonstrates that lead multinational enterprises (MNEs) within GVCs strategically impede functional upgrading—unlike other forms of upgrading—precisely because it challenges their monopolization of intangible knowledge. Consequently, innovation and specialization interact in a far more intricate manner within this functional framework. Innovation can manifest as productivity enhancements, rent-seeking behaviors, or the strategic monopolization of knowledge—encompassing the development of new assets, novel monetization strategies, or deliberate barriers to competitor access. This expanded view of value extraction, particularly from technological assets like brand names, proprietary software, and advanced analytical tools, renders conventional theories of innovation, rooted in cost reduction and output maximization, inadequate for explaining contemporary economic dynamics.

1.6 | Functional Specialization of Industries and Innovation Capacity

The growing importance of intangible assets in GVCs, and their uneven distribution across economic functions, reinforces the need to understand how firms and industries position themselves within value chains. If intangible-intensive functions are associated with greater opportunities for learning, capability accumulation, and value capture, then the relationship between GVC participation and innovation is likely to depend not only on participation itself, but also on the functions performed within the chain. However, the impact of governance on firms participating in GVCs is also mediated by sectoral characteristics and local institutional contexts.

Indeed, the effectiveness of governance arrangements and standards varies substantially across industries: traditional manufacturing, resource-based sectors, complex products, and specialized suppliers each face distinct opportunities and constraints for upgrading. In some sectors, collective efficiency and local institutional support remain crucial, while in others integration into GVCs and compliance with global standards are more **decisive**.

Indeed, the evolution of GVC governance theory—including early contributions—incorporated important insights regarding sectoral differences in learning and innovation patterns. Building on Keith Pavitt (Pavitt, 1984), research demonstrated that sectoral specificities shape both the mode and extent of upgrading in clusters integrated into GVCs.

Traditional manufacturing sectors were characterized as supplier-dominated, where major process innovations are introduced by producers of inputs such as machinery and materials. In these sectors, firms have opportunities to upgrade their products and processes by developing or imitating new product designs, often through interaction with large buyers who increasingly shape the design of final products. Natural resource-based sectors were found to rely crucially on the advancement of basic and applied science, typically undertaken by public research institutes in connection with producers.

Complex products industries were defined by their reliance on high-cost, engineering-intensive products where local networks are typically anchored to leading firms with high design and technological capabilities. The relationships between local suppliers and these anchor firms proved crucial for fostering or hindering firm upgrading through technology and skill transfers. This sectoral analysis revealed that the effectiveness of different governance patterns varies significantly across industries, with important implications for development policy and firm strategy.

The proposed framework is anchored in the recognition that sectoral and industrial specificities fundamentally mediate the durability and efficacy of knowledge monopolization strategies. Sectoral context shapes both the opportunities for, and barriers to, learning and innovation. For example, traditional manufacturing, resource-based sectors, and complex product industries each exhibit distinct patterns of knowledge transfer, learning, and upgrading, as established in classic sectoral innovation studies as we will see in Chapter 4. Such differences reinforce the need for an industry-level analytical perspective, capable of capturing how governance structures, knowledge diffusion, and innovation opportunities vary across sectors and functions. At the same time, they suggest that firms' innovation trajectories depend not only on sectoral positioning, but also on the range and nature of the functions performed within GVCs.

1.6.1 | Intangibles and the Changing Purpose of Innovation

Building on this perspective, an important question concerns how the composition of economic functions influences firms' capacity to innovate. As suggested since Penrose (1959), innovation depends on a broad set of complementary capabilities and intangible assets operating in combination rather than isolation. In this sense, innovation is less the product of a single activity than of a diversified knowledge base embedded across different functions.

Similarly, Montresor & Vezzani (2016) argue that “the multiplicity of intangibles enables the investing firm to embark in the different activities that constitute the innovation process at the firm level” (Montresor & Vezzani, 2016: 333). Again, while the idea of ‘diversification is *good*’ for innovation and profit is not new, its link to functional specialization and the ability to test is new. In the words of Coveri and Zanfei (2023):

[E]xpanding export baskets may not *per se* ensure higher growth opportunities, as these depend to a large extent on the value adding activities performed within industries, **whatever the sectoral disaggregation of the analysis**. In fact, a substantial expansion of the product composition of an economy's export basket may not be associated with higher growth prospects if combined with a specialization in the least value adding activities of GVCs. [...] greater attention should be placed on the functional diversification of economies, namely the ability of countries to carry out a wider range of value adding functions (Coveri & Zanfei, 2023: 84, emphasis added)

They specify at least two critical causal mechanisms linking the breadth of an economic geography's specialization profile and growth: innovation capacity and resilience to shock. While the latter falls just outside the scope of this study, the former is the very subject of it.

An understated lesson drawn from the existing conceptual and empirical literature points to the dangers of hyper specialization on innovation stagnation:

[T]he economy-wide specialization in a circumscribed set of activities can result into a narrower production matrix, reduced learning opportunities and a lower amount of tacit knowledge circulating across domestic actors. This entails the risk of hindering the capability of economies to generate innovation in the long run and should lead to a more careful assessment of the expected gains from the GVC-induced hyper-specialization (ibid, 82).

This argument directly concerns this study. In Chapter 3, evidence is presented from the Sectoral Innovation Database and FDI Markets, which contributes to the idea that functional diversification at the industry level is associated with higher innovation rates in the EU's 5 largest economies, but only in the service not manufacturing sector.

Concerning the difference by sectors, an important contribution that Coveri and Zanfei (2023) builds off is Pisano & Shih (2009), which documents a pattern in U.S. data in terms of a domino-effect of offshoring functions, showing that the pattern usually starts with manufacturing, which itself is not associated with value loss, but follows with offshoring other intangible-intensive functions—namely, design and engineering activities related to high-tech components. In fact, various studies show that the separation of preproduction (eg. R&D) and production functions (eg. manufacturing) could be detrimental to long-term innovation and value capture as sensitive feedback loops are interrupted, leading to failed change management in business (Ketokivi and Ali-Yrkkö: 2009; Zirpoli and Becker:

2011; Pisano and Shih: 2012, and Buciuni and Finotto: 2016). As such, a second axis of analysis in the specialization-value nexus concerns functional configuration: the idea that combinations of specialization yield emergent returns to *scope* in terms of increases in innovation capacity.

The most well-documented *emergent* functional configuration has to do with the combination of preproduction and production activities—the so called ‘brain and brawn’ hypothesis (Buciuni & Pisano, 2021)—which has been suggested to lead to a feedback loop enabling change management by the economic entity or geography managing both activities. Dedrick et al. (2010) observe that in industries where production is largely commoditized, the capacity to direct R&D and design functions alone appears adequate to sustain innovative outcomes. Buciuni and Pisano (2021) systematically articulate the relationship between value chain structure—specifically the interplay of geographic dispersion and operational control—and the ways in which lead firms generate innovation.¹² The authors convincingly argue that a single, universal GVC innovation model does not exist; rather, diverse GVC structures produce qualitatively different innovation dynamics, patterns of knowledge transfer, and competitive opportunities. Here, the combination of specialization may determine partly the innovation dynamics a firm or economic geography has access to within the same GVC relative to another.

Taken together, these contributions suggest that intangible assets should be understood not merely as enabling factors of transformation, but as strategically deployable assets whose configuration across value chain functions shapes firms’ innovation opportunities, competitive positioning, and capacity for value capture. In this perspective, the organization and governance of economic functions become central to understanding heterogeneity in innovation outcomes across firms, industries, and places. Accordingly, the literature on functional specialization extends beyond a purely descriptive account of industrial reorganization. By emphasizing the uneven distribution of knowledge-intensive functions and the distinctive role of intangible assets, it provides a framework for understanding how patterns of specialization influence innovation capacity, learning opportunities, and the distribution of economic rents within GVCs. More broadly, this perspective suggests that contemporary specialization increasingly reflects the organization of functions and capabilities, rather than products alone.

This shift is particularly important because, whereas the object of specialization in nineteenth- and twentieth-century trade was primarily the product, contemporary firms, industries, regions, and countries increasingly specialize in economic functions instead. For example, as will be show in the coming chapter, 3, relative to each other, Spain is more specialized in research and development functions, the Netherlands in headquarters and data centers, France in design and manufacturing, Germany in sales and logistics, and Italy in design and sales.

Generally, in a product-based classification of GVCs, the primary role of innovation is to increase the quality-time-cost efficiency with which an intermediate product is made or incorporated into the final product. In a functional classification of GVCs, the role of innovation also includes the former, but also extends greatly beyond productivity & efficiency-in-constraint to helping firms and economic geographies extract rents from and maintain monopolistic control over intangible knowledge. This rests on the conceptual idea of operationalization of intangible assets, which is in itself an economic activity that must be practiced and scaled up in the form of ‘intrafirm services’ (Penrose, 1959),

¹² Note that arguments concerning lead firm innovativeness are still relevant despite this studying using inward FDI data. This is because innovation related to greenfield inward investments is likely to be captured in the recipient’s innovation statistics, given the fact that this economic entity is likely to be an offshore subsidiary of the parent firm.

'information rents' (Durand & Milberg, 2020), '*organizational* finance capital' (Serfati, 2008), and legally protected assets' (Pagano, 2014).

1.7 | Conclusions

This PhD dissertation argues that the functional specialization lens—an analytical perspective within GVC research that examines how economic geographies focus on and become experts in specific functions within the value chain, rather than specializing broadly by industry or product—is increasingly becoming calibrated to study innovation capacity in GVCs. By foregrounding value captured in the comparative landscape of intangible asset control by economic units and geographies, the functional lens aligns with recommendations from various bodies of scholarship concerned with studying innovation.

For now, it is important to clearly define, in lay terms, the difference between the 4 concepts that feature heavily throughout the pages of this entire study. These concepts are interrelated. The lines between them are not so clearly drawn as would be ideal for theoretical study; however, for the purposes of clear and obvious borders between empirical measurements, these borders will be defined as follows:

- 1) **Technology** is considered in this PhD dissertation in terms of ‘artifacts’ with ‘trajectories’ and ‘regimes’ that individual firms cannot control and rather must adapt to. The collective innovation efforts of all economic actors certainly act upon a technological ‘regime’, accelerating its rise or replacement by another, however, no one or even collection of firms can individually alter the course of a technological regime’s trajectory, barring highly special circumstances. These circumstances do require an extreme capacity for innovation and would be referred to as ‘invention’ or ‘breakthrough’, which largely fall outside the scope of this study. In other words, while there is certainly overlap between innovation and technology, for the purposes of clear borders between terms, we will relegate technology to the regimes outside the control of any individual firm in normal circumstances. An example of this is AI technology. Innovative firms might find new ways to improve, deploy, or otherwise benefit from AI technology; however, they are not reasonably expected to affect the economic significance of the trajectory of the AI paradigm vis-à-vis economic revenue and productivity in any meaningful way.
- 2) **Innovation** is considered in this PhD dissertation to be a propensity of introducing and adapting to novelty (a capacity, not an outcome, input, or asset). As will be seen in the following chapter, the primary measure of innovation in this project is the Community Innovation Survey’s share of firms within an industry to introduce novel products, processes, or organizational changes. The ‘propensity’ definition of innovation distinguishes itself from outcome-based units of analysis such as upgrading, efficiency-based ones such as productivity, and aligns better with existing scholarship. In the following 2 chapters, it will become apparent how this discussion is not merely semantic and will directly influence this study’s measure of innovation at the industry level.
- 3) **Upgrading** is considered drastically different from innovation in this work: it is defined in terms of function only. Product upgrading or process upgrading are seen as problematic terms that greatly contribute to the conflation of innovation and productivity. When firms or countries introduce new products or processes, it is yet to be seen if these products or processes are an *upgrade* or not. As such, they are better termed as innovations, what they are, at once, reducing or eliminating the teleology inferred by the conflation of the two terms (eg. new product *equals* better economic position). Chapter 4 will unpack the term, ‘upgrading’, as well as the related ‘deepening’, further.

- 4) Finally, **intangibles** in this PhD dissertation, as will be discussed in detail in chapters 2 and 3, are considered assets (though they may come in other forms) insofar as they relate to functional specialization (the key metric used to describe the *type* of an industry's involvement in GVCs. There is also a degree of confusion between innovation and intangibles. This is because there is also an 'asset' view of innovation; and if it is intangible (not a machine or otherwise physical and codified piece of capital), they are one in the same. As such, innovation in this work excludes intangible assets (and all innovative outcomes), as, by the definition above, innovation here is a capacity or a propensity for change, specifically change outside the bounds of the normal, mostly in pursuit of adapting to a new technological regime.

Having defined these key, highly conflated terms, the purpose this study can be restated in the following terms: what is the association between GVC participation and innovation capacity in the EU? Does innovation benefit from the simple fact of participation or are functional positions better than others? What are they? Which functional positions of industries are associated with which propensities for innovation? What factors seem to mitigate 'upgrading' in EU industries given the functional position of those industries?

Overall, this chapter has argued that the function performed within GVCs should be treated as a central analytical dimension in understanding whether—and how—participation fosters innovation. Innovation capacity emerges not simply from participation itself, but from firms' ability to generate, absorb, and deploy intangible knowledge as internal skill and routines that, over time, compound to a competitive advantage. In this sense, functional upgrading appears as a cumulative and path-dependent process, shaped by governance structures, learning opportunities, and access to intangible-intensive activities.

At the same time, analyzing these dynamics raises an important methodological challenge: while innovation capacity and functional specialization originate at the firm level, their effects are embedded in broader industrial and territorial systems characterized by knowledge spillovers, technological relatedness, and uneven learning opportunities. This motivates the adoption of an industry-level perspective capable of capturing the wider structural conditions under which firm-level innovation unfolds.

The following chapter therefore introduces the data and indicators used to examine how different patterns of functional specialization relate to heterogeneous innovation outcomes across industries participating in GVCs. Specifically, it leverages data from the Community Innovation Survey (CIS), a firm-level survey administered across European economies, which provides detailed information on firms' innovation activities. By aggregating these firm-level responses—particularly indicators related to the introduction of product, process, and organizational innovations—it becomes possible to construct measures of innovation propensity at the industry level. These measures offer a proxy for the underlying innovation capacity of different industries, while still being grounded in firm-level behavior.

Chapter 1 References

- Altenburg, T. (2006) Governance Patterns in Value Chains and their Development Impact. *The European Journal of Development Research*, 18(4), 498–521
- Ambos, B., Brandl, K., Perri, A., & Scalera, V. G. (2021). The Nature of Innovation in Global Value Chains. *Journal of World Business*, 56
- Andreoni, A. & Boys, J. (2023). Upgrading through Global, Regional, or National Value Chains. Firm-Level Evidence from East African Textiles and Apparel Sector. *Geoforum*
- Antras, P. & Chor, D. (2021). Global Value Chains. In Handbook of International Economics, 5th ED, 1-104
- Bair, J. & Gereffi, G. (2001). Local Clusters in Global Chains: the Causes and Consequences of Export Dynamism in Torreon's Blue Jeans Industry. *World Development*, 29:11, 1885-1903
- Baldwin, R. & Evenett, S. (2015). Value Creation and Trade in 21st Century Manufacturing. *Journal of Regional Science*, 55:1, 31-50
- Benischke, M. H., Buckley, P. J., & Doh, J. P. (2017). Towards a Renaissance in International Business Research? Big Questions, Grand Challenges, and the Future of IB Scholarship. *Journal of International Business Studies*, 48, 1045-1064
- Benson-Rea, M., Gerke, A. & Odlin, D. (2023). SME Upgrading in Emerging Market Clusters: The Case of Taiwan's Bicycle Industry. *Journal of Business Research*, 164, 1-13
- Bernhardt, T. & Pollak, R. (2016). Economic and Social Upgrading Dynamics in Global Manufacturing Value Chains. *Environment and Planning*, 48(7)
- Biondi, Y., & Rebérioux, A. (2012). The Governance of Intangibles: Rethinking Financial Reporting and the Board of Directors. HAL Open Science
- Blair, P. & Miller, R. (2009). Input-Output Analysis: Foundations and Extensions. Cambridge: Cambridge University Press
- Blazek, J. (2016). Towards a Typology of Repositioning Strategies of GVC/GPN Suppliers: The Case of Functional Upgrading and Downgrading. *Journal of Economic Geography*, 16(4), 849-869
- Bontadini, F., Corrado, C., Haskel, J., Iommi, M., & Jona-Lasinio, C. (2023). EUKLEMS & INTANProd: Industry Productive Accounts with Intangibles. Available at https://euklems-intanprod-lee.luiss.it/wp-content/uploads/2023/02/EUKLEMS_INTANProd_D2.3.1.pdf
- Brandl, K. (2017). Direct and Indirect Value Creation in Offshored Knowledge-Intensive Services. *International Journal of Physical Distribution & Logistics Management*, 47:2, 137-155
- Brandt, L., & Thun, E. (2011) Going Mobile in China: Shifting Value Chains and Upgrading in the Mobile Telecom Sector. *International Journal of Technological Learning, Innovation and Development*, 4, 148–180
- Buciuni, G., & Finotto, V. (2016). Innovation in global value chains: Co-location of Production and Development in Italian Low-Tech Industries. *Regional Studies*, 50(12), 2010-2023
- Buciuni, G. & Pisano, G. (2021). Variety of Innovation in Global Value Chains. *Journal of World Business*, 56(2), 1-13. <https://doi.org/10.1016/j.jwb.2020.101167>
- Cafaggi, F et al. (2012). Accessing the Global Value Chain in a Changing Institutional Environment: Comparing Aeronautics and Coffee, IDB Working Paper Series, No. IDB-WP-370, Inter-American Development Bank (IDB), Washington, DC
- Chen, W., Los, B. & Timmer, M. (2018). Factor Incomes in Global Value Chains: The Role of Intangibles. NBER Working Paper 25242
- Clerides, S. K., Lach, S., & Tybout, J. R. (1998). Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco. *The Quarterly Journal of Economics*, 113(3), 903-947

- Cohendet, P. & Simon, L. (2017). Chapter 3: Concepts and Models of Innovation. In Bathelt, H., Cohendet, P., Henn, S., & Simon, L. *The Elgar Companion to Innovation & Knowledge Creation* (Pp. 33-55). Edward Elgar publishing Cheltenham, UK • Northampton, MA, USA DOI 10.4337/9781782548522
- Corrado, C., Hulten, C., & Sichel, D. (2005). Measuring Capital and Technology: An Expanded Framework. In *Measuring Capital in the New Economy*. Chicago: University of Chicago press, 11-46
- Corrado, C., Hulten, C., & Sichel, D. (2006). Intangible Capital and Economic Growth. NBER Working Paper 11948
- Coveri, A. & Zanfei, A. (2022). Functional Division of Labour and Value Capture in Global Value Chains: A New Empirical Assessment Based on FDI Data. *Review of International Political Economy*, 1-28
- Coveri, A. & Zanfei, A. (2023). The Virtues and Limits of Specialization in Global Value Chains: Analysis and Policy Implications. *Journal of Industrial and Business Economics*, 50, 73-90
- Dallas, M., Ponte, S., & Sturgeon, T. (2017). A Typology of Power in Global Value Chains. Copenhagen Business School, CBS. Working Paper / Department of Business and Politics No. 92
- Dallas, M., Ponte, S. & Sturgeon, T. (2019a). Power in Global Value Chains, *Review of International Political Economy*, 26:4, 666-694, DOI: 10.1080/09692290.2019.1608284
- Dallas, M., Ponte, S. & Sturgeon, T. (2019b). Governance and Power in Global Value Chains. In *Handbook on global value chains* (pp. 120-137). Edward Elgar Publishing
- De Marchi, V., Giuliani, E., & Rabellotti, R. (2017). Do Global Value Chains Offer Developing Countries Learning and Innovation Opportunities? *The European Journal of Development Research*, 30(3), 389-407
- De Marchi, V., Di Maria, E., Golini, R., & Perri, A. (2020). Nurturing International Business Research Through Global Value Chains Literature: A Review and Discussion of Future Research Opportunities. *International Business Review*, 29, 1-16
- Durand, C. & Milberg, W. (2020). Intellectual Monopoly and Global Value Chains. *Review of International Political Economy*, 27(2), 404-429. <https://doi.org/10.1080/09692290.2019.1660703>
- Fagerberg, J. & Sapprasert, K. (2011). National Innovation Systems: the Emergence of a New Approach. *Science and Public Policy*, 38(9), 669-679
- Fagerberg, J., Srholec, M., & Verspagen, B. (2010) Innovation and Economic Development. In Bronwyn H. Hall and Rosenberg N. (eds) *Handbook of the Economics of Innovation*, 2, 833–872
- Farole, T. & Winkler, D. (2014). Making Foreign Direct Investment Work for Sub-Saharan Africa Local Spillovers and Competitiveness in Global Value Chains. *Direction in Development: Trade*. Washington, DC: World Bank
- Fernandez-Stark, K., Gereffi, G. (2019). Global Value Chains Analysis: A Primer. In *Handbook on Global Value Chains*, 2nd ED
- Ferriani, S., Lipparini, A., & Lorenzoni, G. (2014). From Core to Periphery and Back: A Study on the Deliberate Shaping of Knowledge Flows and Interfirm Dyads and Networks. *Strategic Management Journal*, 35, 578-595
- Fu, X., Zanello, G., Essegbey, G.O., Hou, J., & Mohnen, P. (2014) Innovation in Low Income Countries: A Survey Report. Oxford: Department of International Development
- Fuentes, A. & Pipkin, S. (2017). Spurred to Upgrade: A Review of Triggers and Consequences of Industrial Upgrading in the Global Value Chain Literature. *World Development*, 98, 536-554
- Gereffi, G. (2014). Global Value Chains in a Post-Washington Consensus World. *Review of International Political Economy*, 21:1, 9-37, DOI: 10.1080/09692290.2012.756414

- Gereffi, G. (2019). Global Value Chains and International Development Policy: Bringing Firms, Networks, and Policy-Engaged Scholarship Back in. *Journal of International Business Policy*, 2, 195-210
- Gereffi, G., Humphrey, J., Sturgeon, T. (2005). The Governance of Global Value Chains. *Review of international Political Economy*, 12:1, 78-104
- Gibbon, P., Bair, J., & Ponte, S. (2008). Governing global value chains: an introduction. *Economy and society*, 37(3), 315-338
- Greenway, D., & Kneller, R. (2007). Industry Differences in the Effect of Export Market Entry: Learning by Exporting? Kiel Institute. DOI: 10.1007/s10290-007-0115-y
- He, Y., Song, M., & Wang, S. (2021). Global Value Chains, Technological Progress, and Environmental Pollution: Inequality Towards Developing Countries. *Journal of Environmental Management*, 277, 1-14
- Hernández-Rodríguez, E., Boschma, R., Morrison, A., & Ye, X. (2025). The role of complementary interregional linkages for functional upgrading and downgrading of global value chains in EU regions. *Industry and Innovation*, 32(9), 1002-1036
- Hopkins, T. K., & Wallerstein, I. (1994). Commodity Chains: Construct and Research. *Commodity chains and global capitalism*, (149), 17
- Humphrey, J., & Schmitz, H. (2002). How Does Insertion in Global Value Chains Affect Upgrading in Industrial Clusters? *Regional Studies*, 36(9), 1017-1027
- Humphrey, J. & Strange, R. (2018). What Lies Between Market and Hierarchy? Insights from Internalization Theory and Global Value Chain Theory. *Journal of International Business Studies*, 50, 1401-1413
- Inomata, S., Liesch, P., Meng, B., Mihailova, I., & Suder, G. (2015). The Evolving Geography of Production Hubs and Regional Value Chains Across East Asia: Trade in Value-Added. *Journal of World Business*, 50:3, 404-416
- Kadarusman, Y. (2012) Knowledge Acquisition: Lessons from Local and Global Interaction in the Indonesian Consumer Electronics Sector. *Institutions and Economies*, 4(2), 65-100
- Kali, R., Turkina, E., & Van Assche, A. (2016). Structure and Evolution of Global Cluster Networks: Evidence from the Aerospace Industry. *Journal of Economic Geography*, 16:6, 1211-1234
- Kano, L., Tsang, E., W., K., & Wai-Chung Yeung, H. (2020). Global Value Chains. A Review of the Multidisciplinary Literature. *Journal of International Business Studies*, 51, 577-622
- Ketokivi, M., & Ali-Yrkkö, J. (2009). Unbundling R&D and manufacturing: Postindustrial Myth or Economic Reality?. *Review of Policy Research*, 26(1-2), 35-54
- Kim, L. (1997). Imitation to Innovation. The Dynamics of Korea's Technological Learning. Harvard Business School Press.
- Lema, R., Berger, A., & Schmitz, H. (2013). China's Impact on the Global Wind Power Industry. *Journal of Current Chinese Affairs*, 42(1), 37-69
- Lema, R., Rabellotti, R., & Sampath, P. G. (2018). Innovation Trajectories in Developing Countries: Co-evolution of Global Value Chains and Innovation Systems. *The European Journal of Development Research*, 30, 345-363
- Looi Kee, H., Margarida Fernandes, A., & Winkler, D. (2022). Determinants of Global Value Chain Participation: Cross-Country Evidence. *The World Bank Economic Review*, 36: 2, 329-360
- Lundvall, B., A. (1992). The Learning Economy and the Economics of Hope. Anthem Press, UK, USA
- Martinez, M. & Poole, N. (2004). The Development of Private Fresh Produce Safety Standards: Implications for Developing Mediterranean Exporting Countries. *Food Policy*, 29(3), 229-255
- Masciarelli, F., Doan, H. Q., & Meliciani, V. (2024). Intangible Assets, Global Value Chains, and

- Innovation: Evidence from Vietnamese SMEs. *Industrial and Corporate Change*, 00, 1-29
- Melendez, M., & Uribe, M. J. (2012) International Product Fragmentation and the Insertion of Latin America and the Caribbean in Global Production Networks: Colombian Case Studies. Washington, DC: Inter-American Development Bank Working Paper No. IDB-WP-374
- Meyer, K. E., & Sinani, E. (2002). Identifying Spillovers of Technology Transfer from FDI: the Case of Estonia. Obtained from <https://research-api.cbs.dk/ws/portalfiles/portal/59008864/7057.pdf>
- Morrisson, A., Pietrobelli, C., & Rabellotti, R. (2008). Global Value Chains and Technological Capabilities: A Framework to Study Learning and Innovation in Developing Countries. *Oxford Development Studies*, 36:1, 39-58
- Nelson, R. (1993). National Innovation Systems: A Comparative Analysis. Oxford University Press. New York
- OECD. (2020). Trade Policy Implications of Global Value Chains. *OECD*. Retrieved from [OECD publications](https://www.oecd.org/publications/).
- Padilla-Perez, R. (ed). (2014). Strengthening Value Chains as an Industrial Policy Instrument. Methodology and experience of ECLAC in Central America. Santiago: Economic Commission for Latin America and the Caribbean (ECLAC)
- Pagano, U. (2014). The Crisis of Intellectual Monopoly Capitalism. *Cambridge Journal of Economics*, 38:6, 1409-1429
- Pavitt, K. (1984). Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory. *Research policy*, 13(6), 343-373
- Penrose, E. (1959). The Theory of the Growth of the Firm. New York, NY: John Wiley
- Pietrobelli, C. & Rabellotti, R. (2011). Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? *World Development*, 39, 1261-1269
- Pisano, G. & Shih, W. (2012). Producing Prosperity: Why America Needs a Manufacturing Renaissance. *Harvard Business Press*
- Serfati, C. (2008). Financial Dimensions of Transnational Corporations, Global Value Chain and Technological Innovation. *Journal of Innovation Economics & Management*, 2(2), 35-61
- Schmitz, H. (2006) Learning and Earning in Global Garment and Footwear Chains. *The European Journal of Development Research*, 18(4), 546–571
- Schumpeter, J. A. (1934). The Theory of Economic Development: An inquiry Into Profits, Capital, Credit, Interest, and the Business Cycle. Cambridge, MA: Harvard University Press
- Schumpeter, J. A. (1942). Capitalism, Socialism, and Democracy. New York, NY: Harper & Brothers
- Solow, R. (1987). We'd Better Watch Out. New York Times Book Review. P. 36. Retrieved from <https://www.standupeconomist.com/pdf/misc/solow-computer-productivity.pdf>
- Song, M. & Wang, S. (2017). Participation in Global Value Chain and Green Technology Progress: Evidence From Big Data of Chinese Enterprises. *Environmental Science and Pollution Research*, 24, 1648-1661
- Sturgeon, T.J., & Kawakami, M. (2011) Global Value Chains in the Electronics Industry: Characteristics, Crisis, and Upgrading Opportunities for Firms from Developing Countries. *International Journal of Technological Learning, Innovation and Development*, 4(1/2/3), 120–147
- Teece, D. (2025). The Multinational Enterprise, Capabilities, and Digitalization: Governance and Growth with World Disorder. *Journal of International Business Studies*, 56, 7-22
- Timmer, M. (2017). Productivity Measurement in Global Value Chains. *International Productivity Monitor*, 33, 182-193
- Timmer, M., de Vries, G. J., & Miroudot, S. (2019). Functional Specialization in Trade. *Journal of Economic Geography*, 19, 1-30
- Wagner, J. (2007). Exports and Productivity: A Survey of the Evidence from Firm-Level Data. *The*

- World Economy*, 30(1), 60-82
- WBG, Cirera, X., & Muzi, S. (2016). Measuring Firm-Level Innovation Using Short Questionnaires: Evidence from an Experiment. Policy Research Working Paper 7696 by Trade and Competitiveness Global practice Group
- Zirpoli, F., & Becker, M. C. (2011). The limits of design and engineering outsourcing: performance integration and the unfulfilled promises of modularity. *R&D Management*, 41(1), 21-43

Chapter 2 | Summary Statistics: Inward FDIs & Industry Innovativeness

2.0 | Executive Summary and Chapter Roadmap

This chapter sets up the empirical strategy used in Chapters 3 and 4, including summarizing key statistical insights from the 2 main datasets used: FDI Markets (FDI-M) and the Sectoral Innovation Database (SID). Key questions asked and answered by this chapter include: how did innovation and inward FDI patterns change over time in Germany (DE), Spain (ES), France (FR), Italy (IT), and the Netherlands (NL)? What are the main differences by industry, country, and business function? And which industries show a higher or lower propensity to introduce different types of innovation?

The inclusion of FDI data reflects the way this dissertation measures the functional specialization (FS) of industries in GVCs, namely through a Balassa (1965)-type index based on inward FDI data. While this chapter introduces and describes the FDI dataset, the calculation and discussion of the specialization index itself are presented in Chapter 3.

FDI-M data is based on greenfield FDIs only, reflecting the “equity participation of MNCs in the different locations where they operate” (Coveri et al., 2024: 6). However, it can be said that this data also captures a great deal of **comparative advantage of geographies** “as defined by available technologies and factor endowments” (ibid). In other words, while in a narrow sense only reflecting a sub-type of GVC, “one might fairly assume that [...] inward FDI-based indicators of functional specialization largely reflect the actual involvement of regions in GVC stages” (ibid).

The ultimate purpose of this chapter is to familiarize the reader with the two individual datasets and how they are merged, the variables used in the empirical examinations in chapters 3 and 4, and to summarize key trends in these variables across the 4 dimensions of country, industry, function, and time. To that end, the rest of this chapter is organized as follows: section 3.1 introduces the SID, justifying its compatibility with the recommendations of Chapter 1. Section 3.2 explains the protocol used to merge the FDI Markets and SID across the dimensions of time, country, and industry. Section 3.3 presents stylized summary statistics for the key indicator of ‘number of inward FDIs’ by country, time, industry, and function. Section 3.4 presents summary statistics for top European Economies’ propensities for innovation between 1994 and 2016. Finally, section 5 concludes, restating the most important findings from the data, which are:

- Apart from the years impacted by the 2008 Financial Collapse, every year exhibits an increase from the year prior in terms of inward FDIs.
- 16,084 FDIs were received between 2003 and 2018 (2016). Of which, Germany received 42%, France 24%, Spain 17%, the Netherlands 10%, and Italy 7%.
- All functions across all industries and countries boast highly consistent increases in inward FDIs over time, except for production functions.
- Germany’s FDI inflows in support functions exhibit the largest singular increase, starting below 100 in 2003 and ending with just under 600 in 2018.
- The functions that received the largest FDI inflows are sales, marketing, and support: 6,198, manufacturing: 2,725, business services: 2,485, logistics, distribution, and transport: 1,399, and headquarters: 1,078.
- The functions that received the fewest FDI inflows are extraction: 7—a function only possible for industry C20: chemical extraction—electricity: 9, shared services centers: 35, recycling: 41, and customer contact centers: 56.

- The publishing industry received the most FDIs with 2,274 total, following by computer and electronic manufacturing: 1,625, the manufacture of machinery and equipment: 1,196, computer programming and information services: 883, and then legal/accounting and consultancy activities: 868.
- The Fewest FDIs were received by industries of trade and repair of vehicles: 5, printing of recorded media: 26, courier activities: 42, wholesale trade: 55, and water transport: 79.
- Innovation patterns have generally become more concentrated over time with earlier periods (1994-2000) typically showing more dispersed distributions and recent periods (2012-2016) showing more similarity across different types of innovation performance over time.
- The most generally innovative country is Germany with very few industries containing less than 50% of firms introducing general innovations on average over time. Italy and Spain seem to be the least innovative countries, with France and the Netherlands landing between these two extremes.
- Across all innovation forms, the industries with the highest aggregate propensity for innovation in Europe between 1994 and 2016 are SB: Science Based industries, and the ones with the lowest capacity for innovation are SD: Supplier Dominated industries. SII and SS industries record similar innovation performances across all forms of innovation capacity except for process innovation, which in general is the category that shows the lowest innovation rates in Europe, perhaps because of being tied to commonly outsourced production functions where Europe does not typically specialize.

2.1 | Introduction: Data Strategy

In the previous Chapter, a review of the literature on innovation and GVC participation was conducted with the explicit purpose of answering the question *why and how* to study innovation in the context and framework of global value chains (GVCs). The chapter found that scholarly treatments of innovation from within dedicated fields of study increasingly converge to a notion of a process that happens increasingly *between* and decreasingly *within* economic firms and countries in complex interactive environments, which are themselves becoming increasingly globalized—i.e. “in a GVC context” (Ambos et al., 2021: 3). Moreover, the discussions also showed that, given its basis on intangible knowledge assets, the increasingly adopted functional approach to specializations in GVCs is suited capable to the study of innovation capacities comparatively between industries involved in global value chains.

Within this context, a disconnect remains between the fields of “economics, econometrics, and finance,” which, according to a literature audit by De Marchi et al. (2020), account for 22.7% of the total contributions on GVC, and other fields such as “social sciences” and “business, management, and accounting,” accounting respectively for 19.6% and 18.5% of scholarly contributions on GVC as of 03/2020 (De Marchi et al., 2020: 13). The problem, as documented in Chapter 1, is that **econometric and finance studies commonly adopt what could be considered an ontologically outdated view on innovation** as a static and homogenous event that can be directly inferred from data on expenditures on a narrow set of inputs or deduced from improved GVC positioning (upgrading).

Chapter 1 argued that much of the critical literature on innovation in GVCs points toward a shift in analytical focus: away from approaches that infer innovation indirectly through aggregate productivity outcomes or broad macroeconomic indicators, and toward the dynamic and heterogeneous processes of capability building occurring at the firm level. In other words, understanding innovation in GVCs requires greater attention not only to whether innovation occurs, but also to where, how, and through which mechanisms firms learn and accumulate capabilities.

Ideally, an empirical analysis of innovation in GVCs would therefore observe firm-level learning processes directly, tracing the specific channels through which knowledge is transferred and capabilities are accumulated. The literature identifies a wide range of such mechanisms, including imitation (Kim, 1997; Kadarusman, 2012), technology spillovers (Kokko et al., 1996; Meyer & Sinani, 2002; Farole & Winkler, 2014), Face-to-Face learning interactions (Altenburg, 2006), formal inter-firm collaborations (Cafaggi et al., 2012), training organized by lead firms (Sturgeon & Kawakami, 2011; Kadarusman, 2012), direct technology transfer (Schmitz, 2006; Fagerberg et al., 2010; Melendez & Uribe, 2012), supplier-buyer relationships (Lema et al., 2013), Industry associations (Ferriani et al., 2014); reverse engineering (Altenburg et al., 2008), employee mobility for training (Kadarusman, 2011; Fu et al., 2014), and compliance with standards as a form of learning (Sturgeon and Kawakami, 2011; Brandt & Thun, 2011; Kadarusman, 2012; Padilla-Perez, 2014).

However, such an approach would be less suited to the broader objective of this dissertation, namely to investigate how patterns of functional specialization relate to heterogeneous innovation outcomes across industries and countries. Addressing this question requires a level of comparability and analytical consistency that is more readily achieved through harmonized industry-level data.

Moreover, the theoretical framework developed in Chapter 1 suggests that innovation in GVCs is not solely a firm-specific phenomenon, but one embedded in wider sectoral and territorial systems characterized by knowledge spillovers, supplier–buyer interactions, technological relatedness, and

function-specific learning opportunities. An industry-level perspective therefore offers an appropriate lens for capturing these broader structural dynamics.

While this study does not directly employ firm-level microdata, it nevertheless incorporates the capabilities dimension of innovation through industry-level indicators derived from the Sectoral Innovation Database (SID) and the Community Innovation Survey (CIS). These indicators measure the share of firms introducing different forms of innovation within each industry, based on representative firm-level survey responses across European economies. Accordingly, the proportion of innovative firms within an industry is interpreted as a proxy for that industry's underlying innovation propensity or capacity. Although the empirical analysis is conducted at the industry level, its foundation in firm-level responses ensures consistency with the innovation-as-capability perspective developed in Chapter 1.

As discussed in the previous chapter, this dissertation adopts a capacity-based approach to the conceptualization and empirical measurement of innovation. Rather than treating innovation as a set of isolated events, innovation capacity is understood as a propensity to introduce novelty into products, processes, or organizational practices.

The Community Innovation Survey (CIS) provides information on firm-level innovation events, namely instances in which firms introduce product, process, or organizational innovations. While single innovation events are of limited analytical value for the purposes of this study, their aggregation at the industry level offers a useful proxy for underlying innovation capacity. More specifically, the share of firms introducing innovation within a given industry is interpreted as an indicator of that industry's propensity to innovate.

This industry-level perspective is particularly appropriate given the objectives of the dissertation. Since innovation in GVCs is shaped not only by firm-specific characteristics but also by broader sectoral learning environments, spillovers, and patterns of interaction, aggregating firm-level evidence allows for a more comprehensive assessment of innovation dynamics while retaining an empirical grounding in firm behaviour. Against this backdrop, the remainder of this chapter introduces the Sectoral Innovation Database (SID), discusses its temporal and industry structure, and presents the CIS-based indicators used throughout the empirical analysis.

The information in this section is directly taken from *The Sectoral Innovation Database 1994-2016* which was built by Pianta, Coveri, and Reljic (2021). Especially important are the authors' insights concerning the time-dimension, the measurement of innovation, and the notes of the relevance of industry level analysis, which are summarized in this section to illustrate the unique ability of the SID to carry out reliable quantitative studies on innovation.

2.1.1 | Industry-Level Benefits

One of the key strengths of the SID is the industry focus. In addition to offering an added layer of granularity whilst maintaining policy and macroeconomic relevance, this meso level approach to data analysis has several desirable characteristics. Of particular interest to this study are these supply (firm) side characteristics—namely:

- (1) The ability to draw from firm-level data (due to the nature of the CIS)
- (2) Alignment with the 'systems' approach
- (3) The ability to bifurcate firms by the Pavitt taxonomy given the organization by NACE 2.

In the words of the authors:

[I]ndustry-level analysis is coherent with the perspective suggested by the literature on sectoral systems of innovation, which stressed that the innovative behaviour of firms is fundamentally affected by the technological regime of the industry they belong to (Malerba 2002, 2004a, 2004b). More precisely, **technological regimes** – defined in terms of **appropriability of innovations, cumulativeness of technological advances, technological opportunities and knowledge nature of firms’ innovative efforts** – shape the **trajectories of innovation** and thus determine the structure of the markets as well as the rate and direction of technological change of industries (Breschi et al. 2000; Malerba 2005; Malerba and Orsenigo 1997). [...] Consistently with this framework, evolutionary approaches developed a meaningful classification of industries, framing them within a limited number of classes according to the technological paradigm they share (Dosi 1982, 1988). Such a framework led to the construction of taxonomies of industries [...] Bogliacino and Pianta (2010, 2016) investigated the relationships between innovation patterns and economic performance of service industries and provided a Revised Pavitt Taxonomy which extends the original Pavitt classification to the service sectors (Pianta et al., 2021: 6).

In total, 41 industries are captured in the SID, split into 18 manufacturing and 23 services industries, each belonging to one of 4 Revised Pavitt Taxonomies (see table 1 below). As will be shown in the coming pages, this classification is very useful for (1) controlling for industry fixed effects, (2) increasing aggregation for higher statistical significance in empirical analysis without losing meaningful industry differences, and (3) observing structural change over time. Table 1 describes the revised Pavitt taxonomy in greater detail; however, a much more extensive discussion is present in [section 4.1.2](#).

Table 1. The Revised Pavitt Taxonomy

Industry Type	Definition and Key Innovation Characteristics	Example Industry
Science Based (SB)	Industries draw their core competencies from scientific and R&D knowledge, often produced internally in laboratories or absorbed from public research institutions. Innovation in this group is dominated by product innovations, which open new markets and underpin technological competitiveness rather than cost reduction. These industries exhibit high R&D intensity, a constant drive to exploit emerging scientific opportunities, and a strong complementarity between science and production	C26: Manufacture of Computer, Electronic, and Optical Products; J61: Telecommunications
Supplier Dominated (SD)	Traditional manufacturing and low-tech service industries that show minimal internal R&D. Their innovation capacity depends on the technological inputs from upstream producers: capital goods, ICT tools, and intermediate products. Their primary strategy is adoption, not generation, meaning innovation enters through supplier linkages	C10-C12: Manufacture of Food Products, Beverages, and Tobacco Products; H52: Warehousing and Support for Transportation
Specialized Supplier (SS)	Industries that produce capital goods, instruments, or technical business services. They innovate through interaction with users rather than purely internal R&D. Product innovation predominates, but it is driven by learning-by-doing, design skills, and incremental technical refinement. Firms are often smaller, highly skilled, and rely on user-producer feedback loops, which make innovation flexible, highly customized, and rapid but confined within technological niches	C30: Manufacture of Transport Equipment; M71: Architectural and Engineering Activities & Technical Testing and Analysis
Scale and Information Intensive (SII)	This category in Pavitt's original classification encompassed industries characterized by economies of scale and dual innovation patterns. Pianta and Bogliacino merge these with information-intensive services—finance, logistics, transportation, and ICT networks—into the new Scale and Information Intensive (SII) class (Pianta & Bogliacino, 2016: 159)	C17: Manufacture of Paper and Paper Products; J58: Publishing Activities

2.1.2| Sourcing Industry Level ‘Capacities’ from Firm-Level Innovation Data

The SID contains 7 innovation variables based on the Community Innovation Survey (CIS) conducted by Eurostat. Specifically, 6 CIS waves are captured, each corresponding to one of the 6 time periods present in the SID: specifically, CIS waves 2, 3, 4, 7, 9, and 10, respectively correspond to the *period: years* of P1: 1994-1996, P2: 1998-2000, P3: 2002-2004, P4: 2008-2010, P5: 2012-2014, and P6: 2014-2016. As explained by the authors:

Community Innovation Surveys provide information which allows disentangling the complexity regarding the process of technological change. On the one hand, it permits to distinguish between product and process innovation, assessing the dominant competitiveness strategies pursued by different industries. On the other hand, it allows to distinguish between the ‘input’ and ‘output’ of innovative efforts; in other words, our database enables to introduce a distinction between the innovative efforts pursued by industries to introduce innovations [...] and the outcome of innovative procedures [...]. These surveys are based on direct questions to firms about their activities: a questionnaire is used, ensuring that definitions of innovations are similar and the procedures of reply are homogenous (Pianta et al., 2021: 12)

Since CIS data is drawn from firm manager responses to standardized questionnaires with strict definitions of the various forms of innovation included, this allows us to *meet the problem halfway*: SID data is industry level data sourced from firm level data and thanks to this it can capture at the industry level some variables that are typically not available at that level, going beyond broad standard statistics like R&D spending and patents, as discussed in Pianta et al. (2021). Given how these firm-level questionnaires are related to one another, the resulting innovation measures can be interpreted as **propensity scores**, capturing the ‘capabilities’/‘capacities’ dimension of innovation. For example, an Industry reporting a process innovation score of, say, 40, is interpreted as an industry whose capacity to innovate is 40%—i.e. it is saying that 40% of firms in that industry introduced innovations in a given time period. If that number were to go up or down over time, or if it is higher or lower in the same industry in a different country, we can interpret that comparatively.

Following Chapter 1, this study adopts a capacity-based approach to innovation. Rather than treating innovation as a series of isolated events, innovation capacity is conceptualized as a propensity: the tendency of firms within an industry to introduce changes to products, processes, or organizational practices. The Community Innovation Survey (CIS) records firm-level innovation events—instances in which firms introduce novelty into their activities. While individual events are not directly analyzed here, their aggregation at the industry level provides a useful proxy for underlying innovation capacity.

Importantly, changes in an industry’s innovation propensity should not be interpreted as a direct measure of changes in the capabilities of individual incumbent firms. For example, an increase in the share of innovative firms within an industry may reflect compositional dynamics—such as the entry of more innovative firms, the exit of less innovative ones, or broader structural adjustments—rather than proportional improvements in the innovative performance of all firms already operating in that industry. In this sense, innovation propensity captures broader industry-level dynamics rather than firm-specific trajectories.

This measure can then be related to the functional profiles of industries in GVCs to examine how different forms of participation are associated with heterogeneous innovation outcomes. Since GVC

integration may reshape the composition and competitive structure of industries over time, an industry-level perspective offers a useful lens through which to observe these broader patterns while remaining grounded in firm-level survey evidence.

2.1.3 | Time Structure of the SID: Schumpeterian Theory of Business Cycle

Given the limited availability of yearly innovation survey data, Pianta et al. (2021) organized the SID database around broader time periods corresponding to “upswings” and “downswings” of business cycles (Pianta et al., 2021: 12). As a result, the SID captures changes in innovation patterns over medium-term economic phases rather than year-by-year fluctuations.

From the perspective of this dissertation, this temporal structure is well suited to the study of innovation and structural change in GVCs. As discussed in Chapter 1, innovation capacity is understood as a cumulative and path-dependent process shaped by successive technological trajectories, learning dynamics, and periods of adjustment. Observing industries across broader business-cycle phases therefore provides a useful framework for analyzing changes in innovation propensity and functional specialization over time, while avoiding excessive emphasis on short-term volatility:

[T]he Schumpeterian theory of the business cycle (Schumpeter 1939) puts major emphasis on the role of investments in technological innovation as the element that governs the succession of development stages of capitalism. According to Schumpeter’s vision, the ability and the rent-seeking attitude of entrepreneurs leads them to introduce disruptive innovations which kick off great investment opportunities and lay the foundations for a new phase of development. The introduction of innovations makes it possible to obtain extra-profits which, in turn, are the engine that triggers economic growth as well as further investments by the mass of potential imitators. Once the previously introduced technological innovation has become pervasive, reaching an advanced stage of diffusion, the most intense competition (due to the high number of imitators and the emergence of diminishing returns) tends to reduce monopolistic profits, while the sectors producing innovative products tend to become saturated, thus discouraging further investments (Pianta et al., 2021: 26).

Due to the SID’s ability to account for different phases of business cycles, it can investigate relationships between and within different technological regimes, heterogeneous impacts of GVC on innovation, and a variety of dynamic trends that change over time depending on the position of the business cycle. Particularly relevant to chapter 4 of the present work is the examination of the association between short term structural change and continuity on the one hand and innovation performance on the other. That said, one drawback of the ‘periods’ approach as compared with individual ‘years’ has to do with the meaning given to the groupings of years, which, as will be discussed in chapter 4, must be done with care and with adherence to known theoretical cutoffs and baselines (it must make historical and economic sense).

2.2| Data Strategy: FDI Markets and SID Merger

Collectively, the CIS-based innovation measures, the industry level approach, and the time structure of the SID contribute a great deal towards attaining the type of innovation study set out in chapter 1 and based on the recommendation of dedicated fields of innovation study (see 1.2.1). However, to study innovation as resulting from interactions between firms in a disintegrated global system of production across borders, the proxy measure of GVC integration must also align with the literature reviewed previously. As such, the data about functions performed is sourced from the FDI Market database and merged with the SID in the manner described in this section.

The Time Dimension: Period Clusters and Missing Years

Concerning the original databases, the SID contains information on innovation (amongst other variables) by industry in Germany, Spain, France, Italy, and the Netherlands between 1996 and 2016; FDI Markets contains information about 27,718 FDI projects, tagged by Nace Revision 2 industry codes, entering the same countries between 2003 and 2018. When relating the two databases to each other, the time span aligns, except for five years (2006, 2007, 2011, 2017, and 2018), which are dropped from consideration. This is because the time structure of the innovation variables in the SID data does not allow for their inclusion. Instead, the time structures of the FDI data is made consistent with the SID dataset in the following manner:

Period 3 covers the range of years, 2003 - 2005

Period 4 covers the range of years, 2008 - 2010

Period 5 covers the range of years, 2012 - 2014

Period 6 covers the range of years, 2014 – 2016

The FDI Markets data begins in 2003, and so periods 1 and 2 are dropped in the merged dataset. Moreover, strict adherence to the structure of the SID would have induced us to include only the years 2003 and 2004 in period 3 as this period corresponds to the Community Innovation Survey 4 (CIS 4: 2002-2004). However, a decision to include 2005 as well was made to ensure that every period covers the same number of years (3 in total). **Since the primary measure here is the number of FDI's, the periods would have been rendered incomparable (at least in the case of period 3) should there be unequal time spans for every period.** (Please refer to the SID methodological notes, Pp.28-29, in Pianta et al. (2021) for the exact SID structure). Finally, please also note that year 2014 FDI's are considered twice, in period 5 and period 6 ranges for the same consistency-with-SID-related reasons. These judgement calls have been checked to ensure they do not unilaterally alter results.

The Dimensions of Industry, Country, and Function

The primary metric used is the number of FDI's, rather than the monetary value of FDI's.¹³ The total number of FDI's included in the analysis concerning the merged FDI-SID databases is 16,084 (period

¹³ As mentioned at the outset of the empirical analysis in chapter 3 of this dissertation, there are notable implications for the use of number of FDI's over the monetary value of those FDI's. Most importantly, when inward FDI's are grouped based on their location along the smile curve (pre-production, production, post-production), a pattern emerges such that pre-production functions boast higher FDI values concentrated in fewer FDI projects; while the opposite holds for post-production in that smaller inwards FDI values are spread across larger FDI projects. In other words, post-production projects tend to be many in number but each one smaller in monetary value, while pre-production projects tend to be higher in value but fewer in number. This is a critical point to note, and as is recommended at the end of chapter 3, future studies seeking to replicate these results might begin with reproducing the analysis using the monetary value of FDI's,

3 – period 6), covering 38 out of the 41 industries included in the SID (see table 3 below for the full list of Nace Revision 2 industries included in the merged dataset). Industries, K66, C33, & N, while present in SID, lack FDI inflows entirely and so are dropped at the outset.

Some small manipulations were required to make FDI Markets industry classifications compatible with their SID counterparts. Namely, individual industries are transformed into groupings. The original (individual) Nace codes are incompatible with the SID (grouped) Nace codes, requiring this treatment, which is conducted at the outset.

In this chapter, summary statistics are presented in two forms depending on the context: longitudinal or cross sectional. The latter is more relevant to chapter 3 of this thesis, while the former is relevant to chapter 4. The former is also generally more statistically robust, boasting greater observations per data point due to the higher aggregation, while the latter is more substantively significant, offering greater information in the form of changes over time. Both insights are equally important for the coming analysis.

Herein, five variables are discussed (Table 2). Please note that the FDI variable is not presented in its final form in this Chapter. That will happen in the coming chapter ([section 3.1](#)), wherein the Balassa-type Functional Specialization of Industries Index (FSI) is calculated and presented. In this chapter, we shall consider the underlying raw data on FDIs, which is very important to understand, especially given some of the limitations of the FSI indicator and the degree of heterogeneity of observations in the 5 countries and the 38 industries under examination (Table 3).

Table 2. Variables Included in The Merged Dataset That are Summarized in This Chapter

Variable	Definition	Measurement
<i>fdi</i>	Inward FDI Projects	Number of projects
<i>qinno</i>	General Innovation	Percentage of firms in industry
<i>qinpdt</i>	Product Innovation	Percentage of firms in industry
<i>qinpcs</i>	Process Innovation	Percentage of firms in industry
<i>qinorg</i>	Organization Innovation	Percentage of firms in industry

which, for the sake of simplicity, has been left outside the scope of this work. The treatment of functional profiles in this thesis is geared towards number of FDIs, which is nonetheless quite standard in the literature using the fDi Markets database. However, replication using value of FDIs remains an interesting avenue for future research.

Table 3. 38 Industries, by Nace Revision 2, Included in the Final Dataset

Number	Industry	Nace 2 Code	Pavitt
<i>Manufacturing</i>			
1	Food, Beverage, & Tobacco	C10-C12	SD
2	Textile, Wearing Apparel, & Leather	C13-C15	SD
3	Wood & Cork Products, Except Furniture	C16	SD
4	Paper & Paper Products	C17	SII
5	Printing & Reproduction of Recorded Media	C18	SII
6	Chemicals & Chemical Products	C20	SB
7	Basic Pharma Products & Preparations	C21	SB
8	Rubber & Plastic Products	C22	SII
9	Other Metallic Mineral Products	C23	SII
10	Basic Metals	C24	SII
11	Fabricated Metal Products Except Machinery	C25	SD
12	Computer, Electronic, & Optical Products	C26	SB
13	Electrical Equipment	C27	SS
14	Machinery & Equipment <i>n.e.c</i>	C28	SS
15	Motor Vehicles, Trailers, & Semi Trailers	C29	SII
16	Other Transport Equipment	C30	SS
17	Furniture & Other Manufacturing	C31-C32	SD
<i>Services</i>			
18	Wholesale/Retail Trade & Repair of Vehicles	G45	SD
19	Wholesale Trade, Except of Motor Vehicles	G46	SD
20	Retail Trade, Except of Motor Vehicles	G47	SD
21	Land Transport & Transport via Pipelines	H49	SD
22	Water Transport	H50	SD
23	Air Transport	H51	SD
24	Warehousing & Support for Transportation	H52	SD
25	Postal & Courier Activities	H53	SD
26	Accommodation & Food Service Activities	I	SD
27	Publishing Activities	J58	SII
28	Audiovisual & Broadcasting Activities	J59-J60	SII
29	Telecommunications	J61	SB
30	Programming, Consultancy, & Related Activities	J62-J63	SB
31	Financial Service, Except Insurance & Pension	K64	SII
32	Insurance & Pension Funding	K65	SII
33	Real Estate Activities	L68	SS
34	Legal & Accounting Activities, & Consulting	M69-M70	SS
35	Architecture & Engineering Activities	M71	SS
36	Scientific Research & Development	M72	SB
37	Advertising & Market Research	M73	SS
38	Other Prof. & Scientific Activities, Veterinary	M74-M75	SS

2.3 | Distribution of Inward FDI

2.3.1 | Stylized Summary Statistics: FDI Inflows Over Time & by Country

As shown in figure 1, while the long-term trend in FDI inflows is an obvious and significant uptrend, the years between 2008 and 2016 show a marked slowdown in FDI growth. The years 2009-2014 exhibit a particular lull with the number of inward FDI hovering horizontally in the 1500-1800 range. This is mostly attributable to the economic slowdown brought on by the Financial Collapse of 2008, which saw the long-term uptrend breaking in the years until sharply regaining momentum first in 2015, and then again in 2017.

Figure 1. Number of Inward FDI by Year (2003-2018) and Country

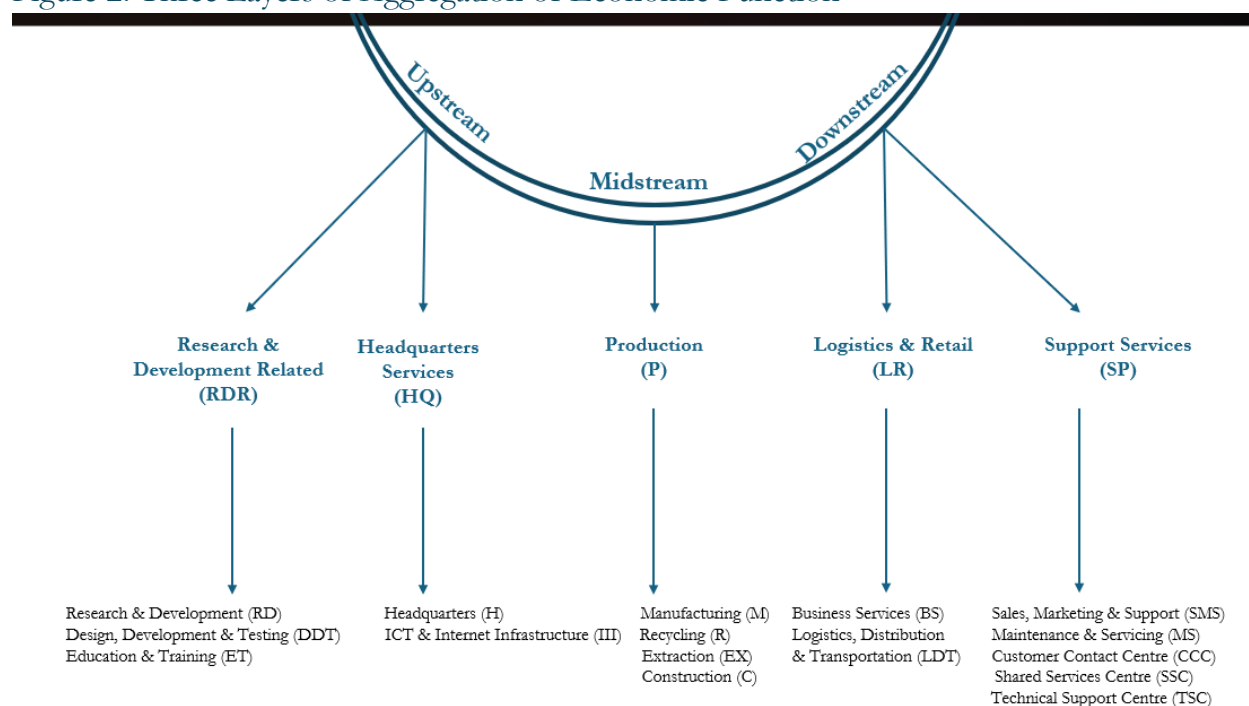


Table 4. Inward FDI by Country

<u>Germany (DE)</u>	<u>France (FR)</u>	<u>Spain (ES)</u>	<u>Netherlands (NL)</u>	<u>Italy (IT)</u>
FDI-M only 10,853 (39%)	FDI-M only 7,133 (26%)	FDI-M only 4,938 (18%)	FDI-M only 2,733 (10%)	FDI-M only 2,061 (7%)
FDI-SID 6,756 (42%)	FDI-SID 3,848 (24%)	FDI-SID 2,717 (17%)	FDI-SID 1,567 (10%)	FDI-SID 1,196 (7%)

Apart from the years impacted by the Collapse, every other year exhibits an increase from the year prior with small and negligible exceptions. In terms of the distribution of inflows by country, the shares are shown in table 4. Figures 3-5 (below) describe the inflows of FDI by function groups over time. An adapted classification protocol was followed wherein 2 modifications were made to Stollinger (2021)'s Narrow Categories: (1) 'construction' is included as part of **production** (instead of being absent); and (2) 'retail' is removed from **logistics**. The first modification to Stollinger (2021) was made as a judgement call following Comotti et al. (2020) and the second modification was necessary due to the absence of a 'retail' function tag in FDI Markets, FDI related to which are instead counted in Sales, Marketing, and Support (see figure 2 below), which is, throughout this entire work, considered as part of the second group of downstream functions—i.e. Support functions. As such, figure 2 below shows the final breakdown of functions at the 3 levels of aggregation.

Figure 2. Three Layers of Aggregation of Economic Function



Figures 3, 4, and 5 below report the number of FDI entering each of the five countries between 2003 and 2016 across three narrow function groups: RDR, P, and SP. HQ and LR are not reported because they are nearly identical to RDR and SP, respectively. This is expected given the EEG argument that functions—especially complex ones—develop concurrently with related functions (e.g. logistics and support). This is not a novel or surprising finding, but it does provide modest support for the underlying logic of the data: that FDI inflows can capture the functional profiles of industries and regions.

At the same time, the figures should be interpreted cautiously and primarily as descriptive evidence. Their purpose is not to establish causal relationships or validate the empirical strategy, but rather to provide an initial overview of the distribution of functional activities across countries and over time. In this sense, the patterns observed offer a useful descriptive backdrop for the functional specialization analysis developed in the following chapter.

In both R&D and HQ related functions (figure 3 and appendix item A¹⁴), Germany leads in terms of absolute number of FDI inflows, which is visually depicted by the **upshifted position** of the German line-of-fit—relative to that of the other countries—and the rate of increase of FDI inflows, which is shown by the **slope of the line**. The Netherlands and Italy exhibit the lowest absolute number of FDI inflows and the least steep slopes (weakest growth) in R&D related functions. In HQ functions, while the same is true of Italy, the Netherlands exhibits a fast rate of growth of FDI inflows with a slope of 2.6, second only to Germany's 3.5. France and Spain lie in the middle of both bounds.

The **R² metric**¹⁵ is the third and final indicator of key interest in the figure, and it shows how consistent the growth in FDI inflows is—i.e. how well the line describes the observed data or how good of a predictor *year* is of *fdi*. In R&D, Germany shows the most consistent growth over time, followed from afar by the Netherlands, France & Spain—in that order—while Italy's growth in R&D cannot be said to be consistent or otherwise as there is essentially 0 growth (slope of 0.4) having gone from around ~ 10 to 15 R&D related FDIs in 16 years. In HQ functions, the same general patterns hold, with exception of the Netherlands, which shows the most consistent growth in HQ related FDIs, possibly hinting at that country's rise as a global HQ hub for GVC integrated industries.

Figure 3. Number of Inwards FDIs in R&D Related Functions Over time

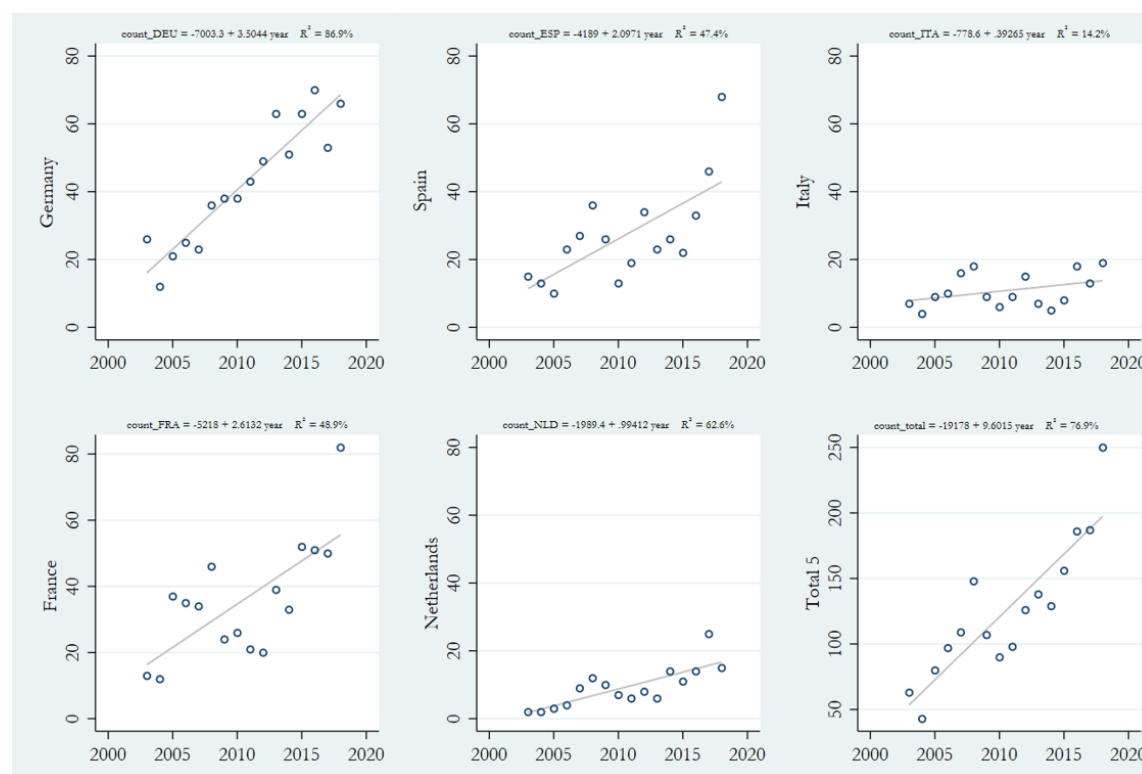


Figure 4 depicts the number of FDIs entering the 5 countries in activities related to production: manufacturing; recycling; extraction (chemical industries only); and construction. France, Spain, &

¹⁴ The aforementioned figures related to HQ and LR functions are reported in the appendix for transparency, having been excluded from the body of this text for being highly redundant with, RD and SP, respectively—as noted prior.

¹⁵ Please note the unusual use of the R-Squared indicator. Here it is used simply to gauge the extent to which FDI inflows increase consistently with time. It should not be taken to mean anything beyond this simple point.

Germany all start the trend with the same number (~80) of FDI inflows related to production functions in 2003. Germany ends the 16-year period with the highest number of FDIs, ~ 140. Italy and the Netherlands show the least absolute number of inflows for this function category as well, both starting and ending the trend with below 40 FDIs per year.

Germany shows the only positive rate of growth of FDI inflows for the production function with a slope of 3.2, which stands in stark contrast to the 0.4 and 0.2 slopes of the Netherlands and France—respectively—and even more so the negative slopes of -0.1 and -1.3 exhibited by the lines of fit in Spain and Italy—respectively. It is not surprising that production function related FDIs are not showing a strong uptrend in Europe, as the continent is not relatively specialized in midstream activities (see chapter 3 findings).

Production-related FDI inflows exhibit heterogeneous temporal patterns across countries. Spain, France, and, to a lesser extent, the Netherlands display relatively stable trends over the period considered. Italy instead records a gradual decline in production-related inward FDIs, while Germany shows a moderate increase, although this pattern may partly reflect a limited number of years characterized by particularly large investment inflows, potentially linked to automotive or advanced manufacturing activities.

Figure 4. Number of Inwards FDIs in Production Functions Over Time



Figure 5. Number of Inwards FDIs in Support Functions Over Time



Overall, Germany appears to display a comparatively more resilient pattern of production-related FDI inflows over the period considered. While caution is warranted in interpreting descriptive trends, this pattern may be broadly consistent with arguments emphasizing complementarities between production and knowledge-intensive activities. As discussed in Chapter 1 through the “brain and brawn” hypothesis, the co-existence of manufacturing and intangible-intensive functions may support learning, adaptation, and the accumulation of capabilities within industries. In this sense, the German case may offer a suggestive illustration of how production activities can remain closely intertwined with broader innovation dynamics rather than becoming fully detached from them.

Finally, figure 5 concerns the support services. Italy shows the weakest performance in terms of the absolute number and rate of FDI growth in logistics functions and support services, in fact showing a moderate decrease in support services over time. The case of Italian support services is interesting due to the fact that it displayed a competitive uptrend before 2008, but, unlike the other countries, it never recovered from the Financial Collapse it seems. There might be reason to believe this recovery began towards the end of the period covered by FDI Markets as the 2017 and 2018 numbers of FDI inflows in both logistic and support categories represent a notable increase from the previous decade of lull.

While Spain and France show a drastic drop in post-production FDIs beginning in 2008, they also display a fast recovery compared to Italy. FDIs related to downstream functions in the Netherlands and Germany were seemingly unaffected by the 2008 Collapse.

The single most standout fact in the figure is Germany’s performance in support functions, starting below 100 in 2003 and ending with just under 600 in 2018. As will be shown later, this is mostly driven by SMS-related FDI inflows.

2.3.2| Stylized Summary Statistics: FDI Inflows by Industry and Function

Given the total population of 16,084 inward FDI projects across all five countries in the merged data, the service industry that received the most FDI projects is J58: Publishing Activities, a low tech, scale intensive industry that received 2,274 FDI projects in the concerned years (SID periods 3, 4, 5, & 6) with Germany receiving the most projects, 937, and Italy the least, 142. The manufacturing industry that received the most projects is C26: Manufacture of Computer, Electronic, and Optical Products, a high tech, supplier dominated industry that received 1,625 total projects. Germany, again, received the most with 757 and Italy the least with 126. The service and manufacturing industries receiving the fewest projects are—respectively—G45 and C18, each recording a negligible amount of FDI projects between 2003 and 2016.

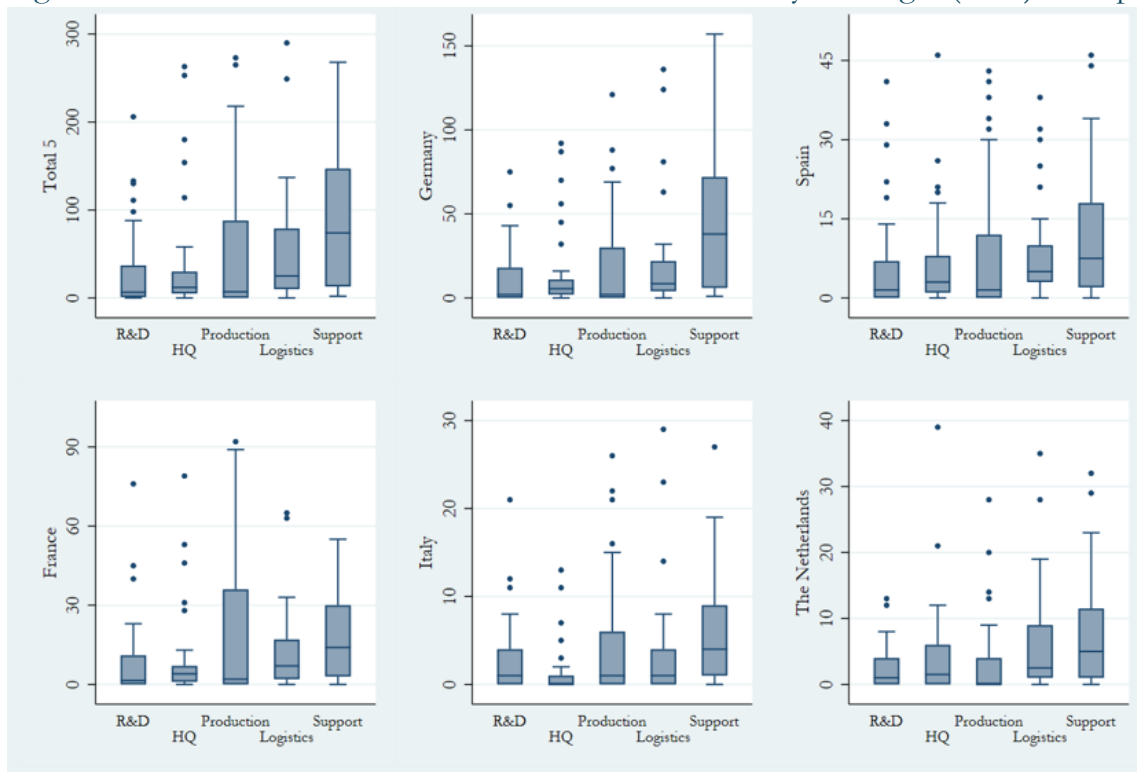
The function that, across all five countries and individually in each of the five received the most FDI projects is Sales, Marketing, & Support (6,198 projects). This greatly drives Europe's specialization in Support Service functions, as per the Stollinger (2021) definition of the narrow categories (groupings) of functional specialization. This is visually depicted in figure 6. The box plots illustrate the distribution of FDI projects across the five 'narrow' functional categories (R&D, HQ, Production, Logistics, Support) for five countries (Germany, Spain, France, Italy, the Netherlands) and the total. Each dot in the box plots is a country-industry pair.

Key observations include:

- **Skewed Distributions:** all categories show strong downstream skewness, with several outliers evident across all countries, particularly in the production, logistics, and support categories.
- **High Variability:** the support and production groups consistently display the widest spread and highest medians across most countries, suggesting greater variability in project counts.
- **Outliers:** all countries exhibit a substantial presence of outliers, indicating occasional large inward FDI counts per some industries (such as J58) inflating the data range.
- **Country Differences:** Germany and France show the highest counts and spread across all categories, while Italy and the Netherlands have lower inward FDI activity with tighter spreads.
- **Functional Insights:** R&D and HQ tend to have lower medians and more consistent distributions, while support and production show greater variability and more outliers.

The overall trend highlights significant cross-country differences and functional imbalances, with downstream functions attracting a higher volume and variation in inward FDI projects.

Figure 6. Cross Sectional Total Number of Inward FDI by Stollinger (2021) Groups



Note: The classification of value chain functions has been adapted from Stollinger (2021). To improve the readability of the figure, a few outliers have been removed.

Concerning number of FDI by industry, publishing activities received the most FDI with 2,274 total, following by computer and electronic manufacturing (1,625), the manufacture of machinery and equipment (1,196), computer programming and information services (883), and then legal/accounting and consultancy activities (868). The least FDI were received by industries related to trade and repair of vehicles (5), printing of recorded media (26), courier activities (42), wholesale trade (55), and water transport (79).

The top industries receiving the most FDI in each country are as follows. Germany is dominated by J58, followed by C26, C28, J62-J63, and C20; Spain's most FDI are in J58, M69-M70, C26, H49, and C29; France consistently record high FDI in J58, C26, C28, J62-J63, and C20; Italy's strongest FDI presence is in J58, C26, M69-M70, K64, and H49; while the Netherlands' Top industries receiving FDI are J58, C26, J62-J63, C20, and M69-M70 (see table 1 for industry Nace codes).

Germany and France show strong focus on J58, C26, and C28, indicating concentration in similar sectors. Spain and Italy show a higher presence of M69-M70 compared to other countries. The Netherlands overlaps with Germany and France but also emphasizes J62-J63 and C20 more prominently. These patterns will become increasingly important in the coming chapter.

2.4| Stylized Summary Statistics: Innovation by Time, Country, and Sector

The Innovation-related variables under analysis are sourced from the Sectoral Innovation Database. Specifically, they are:

Table 5. Innovation Variables Present in the SID

Variable	Description
qinno	Share of firms introducing general innovation (%)
qinpdtd	Share of firms introducing product innovation (%)
qinpdtonly ¹⁶	Share of firms introducing product innovation <u>only</u>
qinpcs	Share of firms introducing process innovation (%)
qinpcsonly ³	Share of firms introducing process innovation <u>only</u>
qinorg	Share of firms introducing org. innovation (%l)
qinorgonly ³	Share of firms introducing org. innovation <u>only</u>

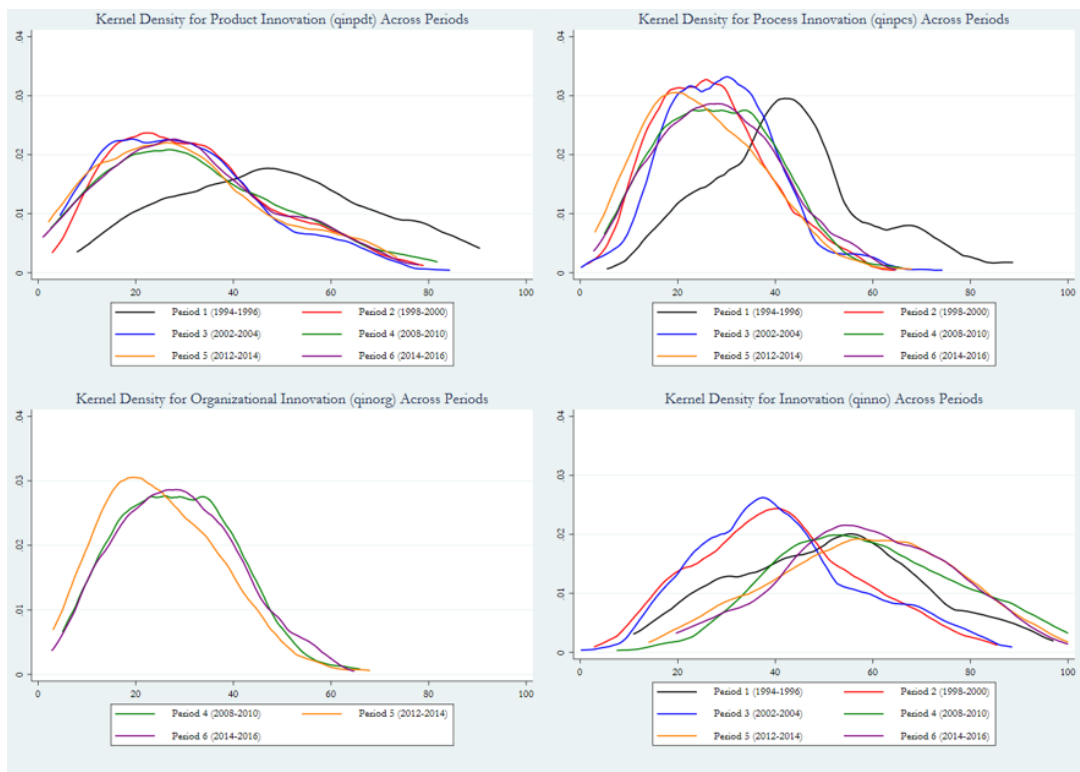
The general, product, process, and organization innovation variables derive from the Community Innovation Surveys, specifically, CIS waves 2, 3, 4, 7, 9, and 10, respectively corresponding to the period: years of P1: 1994-1996, P2: 1998-2000, P3: 2002-2004, P4: 2008-2010, P5: 2012-2014, P6: 2014-2016. **The kernel density plots below in figure 8 show the evolution of different types of innovation across six time periods from 1994 to 2016.**

The distribution of product innovation (**qinpdtd**) shows a gradual shift over time. Period 1 (1994-1996) had a comparatively spread-out distribution with a later peak, while subsequent periods show more concentrated distributions with earlier peaks around the 20-30% mark. The curves become more similar in recent periods (2012-2016), suggesting a stabilization in product innovation patterns. Process innovation (**qinpcs**) displays the most dramatic changes. The earliest period (1994-1996) shows a distinctly different pattern with a later peak of around 40%. Later periods exhibit earlier peaks around 20-25% with higher density, **indicating that process innovation became more concentrated in a smaller range of firms.** The distribution has become narrower in recent periods, **suggesting more uniform process innovation rates across firms.**

Only three periods contain data for organization innovation (**qinorg**), which is to point out that this metric was introduced in later Community Innovation Survey (CIS) waves. The distributions are relatively similar across periods, with peaks around 20-30%. Period 5 (2012-2014) shows a slightly earlier peak and higher density compared to other periods, indicating a temporary increase in organization innovation adoption. The share of general innovators (**qinno**) distribution shows the most complex patterns. Early periods (1994-2004) display higher densities in the middle range (around 40%), while later periods show a flatter, more spread-out distribution. This suggests that innovation became more varied across firms over time, with less concentration around specific adoption rates.

¹⁶ The proportion of European firms that stick to 1 type of innovation exclusively is vanishingly small (hovering around 10% per industry), and the variation displayed by these variables (i.e. the "...only" variables) is severely limited: commonly just 1-3 percentage points. Thus, they are rather outside the main scope and purpose of this work and generally capture little information compared with their unrestricted counterparts. However, some future analyses, as discussed at the end of the empirical chapters 3 and 4, such as those related to innovation 'lock in' and path dependency, might benefit from considering these variables. These works should, however, use theoretically consistent transformations to deal with the lack of variance shown by these variables.

Figure 8. Kernel Densities: Average Share of Firms Introducing Innovations by Period



Key Trends:

- Innovation patterns have generally become more concentrated over time
- Earlier periods typically showed more dispersed distributions
- Recent periods (2012-2016) show more similarity across different types of innovation
- The shift in peaks toward lower percentages suggests a more focused but potentially lower overall rate of innovation adoption
- A degree of convergence seems present across the 4 innovation indicators

Concerning this last point, it is perhaps important to note that general innovation (**qinno**), which includes all types of innovation, is a strong indicator of all types of innovation, with 83% correlation with product and organization innovation (the strongest correlation) and 73% correlation with process innovation. The weakest correlation is between process and organization innovation at 67%, which is still quite high. All these correlations are statistically significant at the highest possible level with data points observed across almost all 38 industries from all 5 countries (total possible *obs* = 1140). Note also that despite having data for only periods 4, 5, and 6, organization innovation still contains 487 total observations (with **qinno** having 960/1140 observations; **qinpd** 902/1140; and **qinpc** 892/1140 *obs*). Since the empirical studies in chapters 3 and 4 exclude the first two periods (as they do not exist in FDI Markets), the *qinorg* variable's lack of inclusion in the early years of the CIS does not severely hinder the analysis by its lack of observations for those years—i.e. the absence of data is 1 out of 4 periods' worth not 3 out of 6.

Given the correlations between general innovation and the other forms of innovation, the following figures 9 and 10, below, can be considered as strongly (though as will be seen in the following chapter, not perfectly) representative of all innovation types:

Figure 9. Histograms: Share of General Innovators by Period (All Industries & Countries)

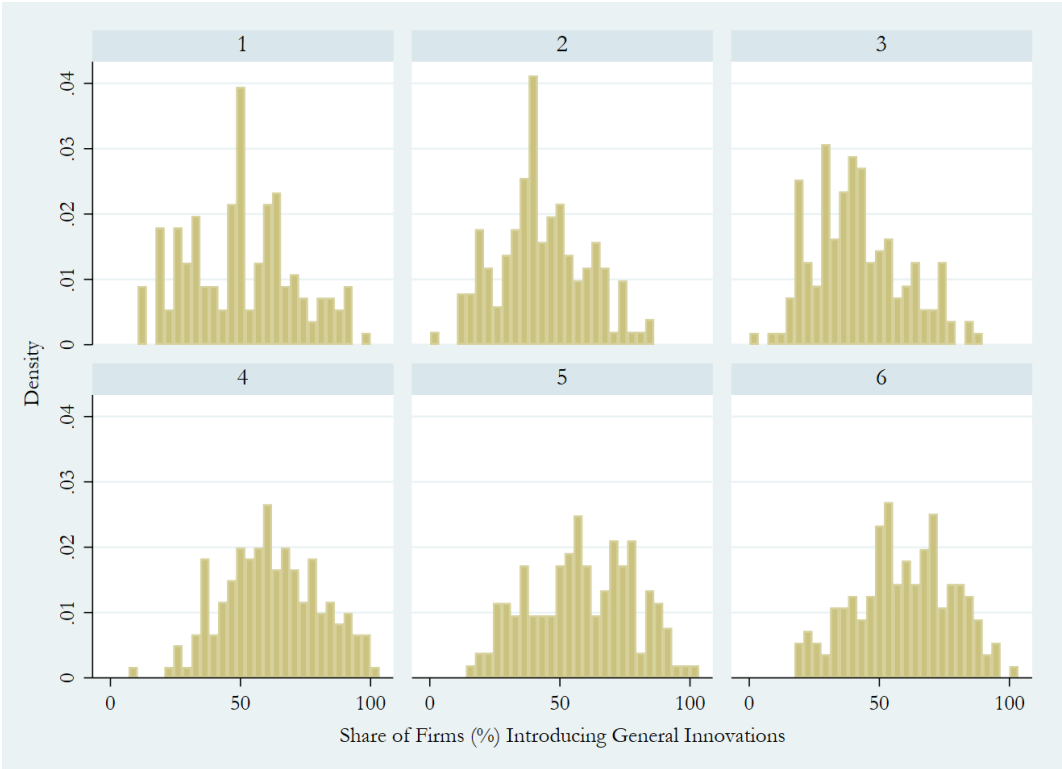


Figure 10. Histograms: Share of General Innovators by Country (All Industries & Periods)

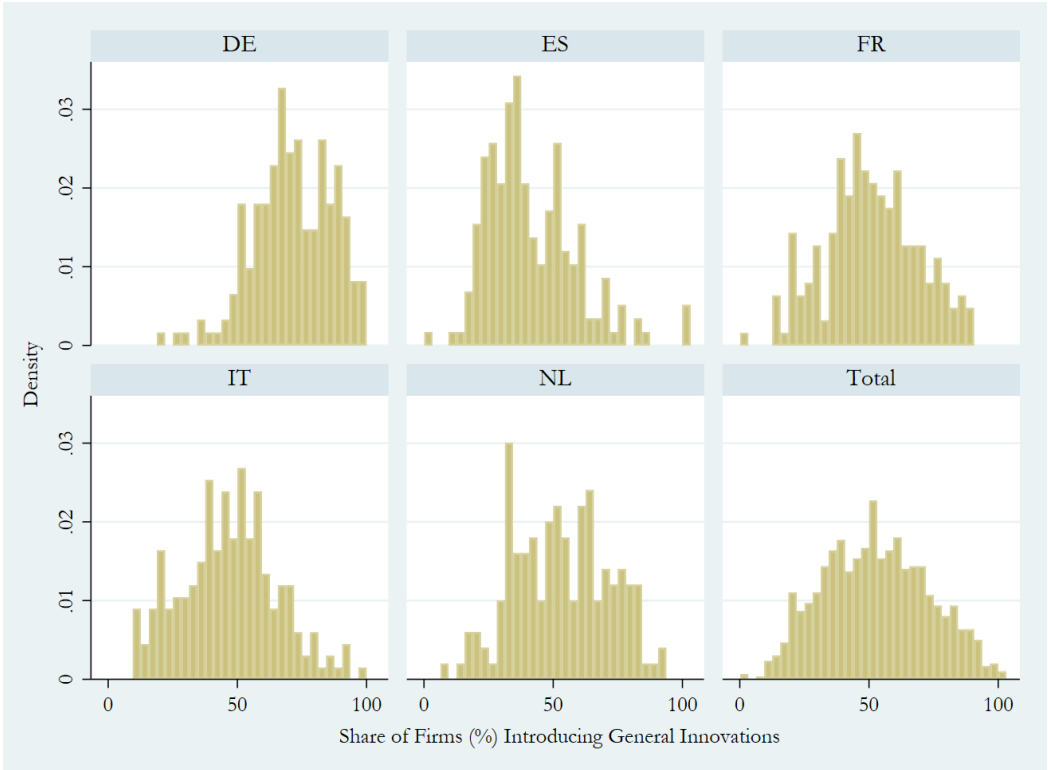


Figure 9 shows the same trend contained in the Kernel Densities in figure 8 with more detail for every period. Time periods 1, 2, and 3, corresponding to 1994-2004, show a leftward shift in innovation performance peaks, meaning a greater concentration of industries containing a smaller percentage of general innovators. The latter years, 4, 5, and 6, corresponding to the years 2005-2016, display much smoother innovation patterns, with shorter peaks, especially along the lower innovation rates (below ~40%), confirming what was shown in figure 9, which is a flatter, more spread-out distribution, suggesting innovation became more varied across firms over time, with less concentration around specific adoption rates.

Aggregating by time, figure 10 shows histograms for the *qinno* variable by country. The total is given for all 5 countries together, showing a markedly normal distribution, with peak concentrations around the 50% mark, indicating a median of around 50% of firms in an average industry being innovative. The most generally innovative country is Germany with very few industries containing less than 50% of firms introducing general innovations on average over time. Italy and Spain are the least innovative countries, with France and the Netherlands landing between these two extremes.

Figures 11 and 12 display innovation patterns by industry and sector (aggregated by country and time). The former shows propensities for all 4 types of innovation by the Revised Pavitt Taxonomy (SB = Science Based; SD = Supplier Dominated; SII = Scale and Information Intensive; and SS = Specialized Supplier). Across all innovation forms, the industries with the highest aggregate propensity for innovation in Europe between 1994 and 2016 are SB: Science Based industries, and the ones with the lowest capacity for innovation are SD: Supplier Dominated industries. SII and SS industries record similar innovation performances across all forms of innovation capacity with the exception of process innovation, which in general is the category that shows the lowest innovation rates in Europe, perhaps because of being tied to commonly outsourced production functions where Europe does not typically specialize (see next chapter).

As was the case with the FDI data, this pattern concerning innovation propensity of industries by the Pavitt classification of industries is not novel evidence; quite the contrary, it is the expected pattern. As such, this is a favorable sign that the CIS-based data is functioning correctly: it is capturing the innovation propensity of industries in the predictable pattern established in perhaps the most dedicated and widely-accepted classifications of industries across innovation lines.

It is interesting that in terms of sectors (figure 12), services constantly underperform manufacturing in all innovation capacities with the smallest discrepancies being in organization related innovations. The biggest discrepancy is in product innovation capacities, where on average over the two decades between 1994 and 2016 in the top European economies, roughly 20% of service industry firms are capable of product innovation as opposed to nearly 40% for manufacturing industries.

Figure 11. Propensity for Various Forms of Innovation by Pavitt, Country, and Time

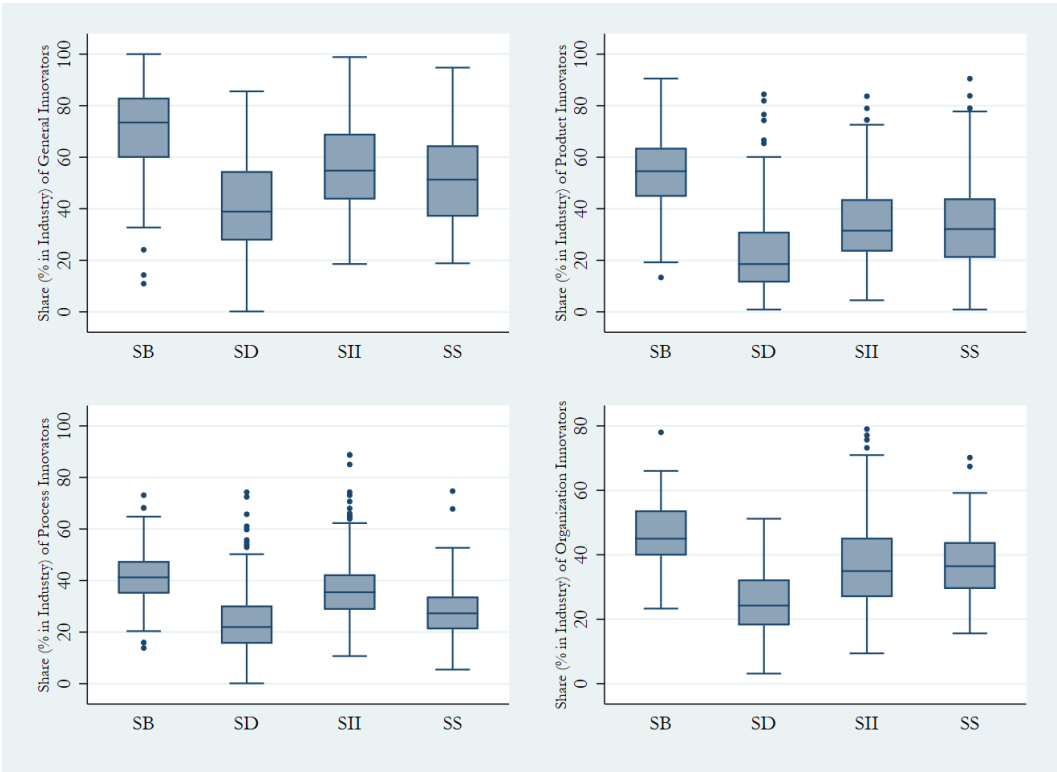
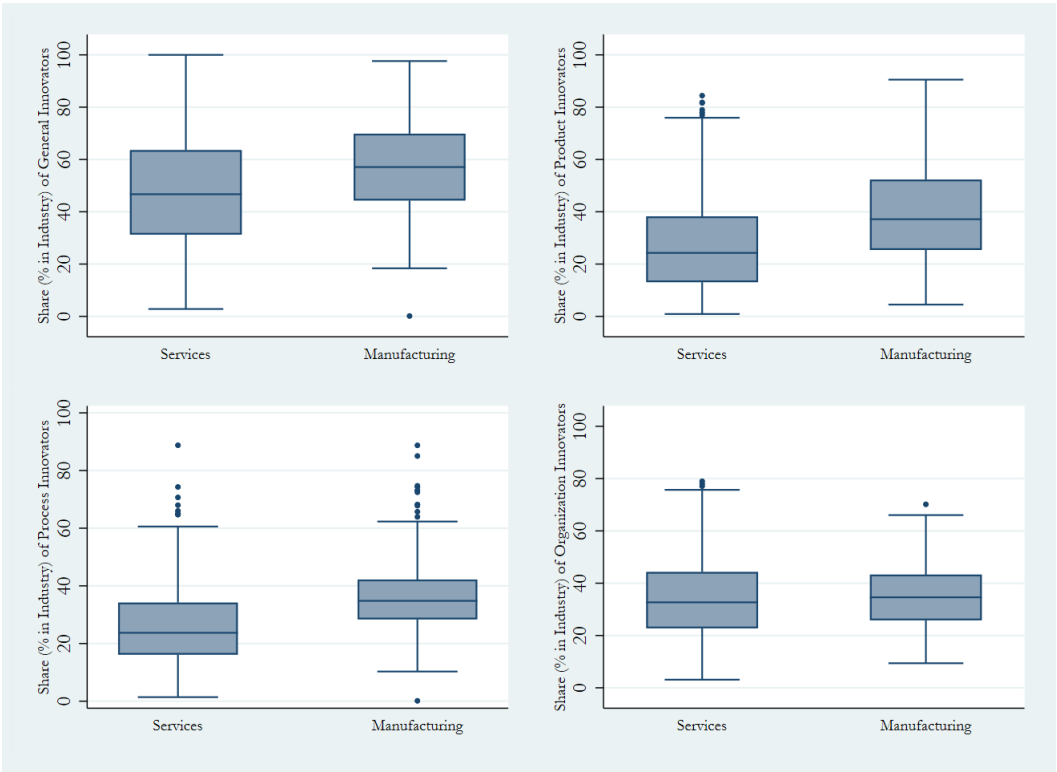


Figure 12. Propensity for Various Forms of Innovation by Sector



The pattern documented in Figure 12 may be relevant considering one of the empirical findings discussed later in the dissertation, namely the heterogeneous relationship between functional diversification and innovation across manufacturing and service industries. While service industries display lower average innovation rates than manufacturing industries, the mechanisms underpinning innovation may differ across the two sectors.

As discussed in Chapter 3, the empirical results suggest that functional diversification is more strongly associated with product and process innovation in services, whereas innovation outcomes in manufacturing appear to be more closely related to factors such as innovation expenditures, economies of scale, and the volume of inward FDI. Although these relationships should be interpreted cautiously, the descriptive patterns reported here are broadly consistent with the possibility that innovation dynamics differ systematically across sectors.

2.5 | Conclusion: Summary of Key Findings

The summary statistics in this chapter do more than describe the empirical terrain of the dissertation; they establish the structural conditions under which Chapters 3 and 4 test the relationship between functional specialization and innovation. Three broad patterns stand out. First, inward FDI in the five EU economies is concentrated in intangible-intensive, pre- and post- production functions, while production functions remain comparatively weak. Second, innovation propensities are not evenly distributed across countries or industries but follow a consistent hierarchy in which Germany is the most innovation-intensive economy, supplier-dominated industries the least innovative, and science-based industries the most dynamic. Third, innovation over time appears increasingly concentrated and less dispersed, suggesting not only a gradual stabilization of innovation behavior but also a possible deepening of functional patterns within European industries. These observations are reinforced with empirical analysis and interpretations in the coming chapter.

What makes these findings especially important is their theoretical implication. The data suggests that Europe's functional structure is asymmetric: it is comparatively strongest in coordination-rich activities, but structurally weakest in production functions. That asymmetry matters because it helps explain why the relationship between GVC participation and innovation cannot be treated as linear or uniform across sectors.

The findings are summarized below for easy reference going forward:

- Apart from the years impacted by the 2008 Financial Collapse, every year exhibits an increase from the year prior in terms of inward FDIs. ([see relevant page](#))
- 27,718 (16,084 in the merged data) FDIs were received between 2003 and 2018 (2016). Of which, Germany received 39% (42%), France 26% (24%), Spain 18% (17%), the Netherlands 10%, and Italy 7%. ([see relevant page](#))
- All functions boast highly consistent increases in inward FDIs over time, except for production functions. ([see relevant page](#))
- Germany's FDI inflows to support functions is singular, starting below 100 in 2003 and ending with just under 600 in 2018. This fact gains significant importance in chapter 3 in the discussion concerning returns to scale in the specialization-innovation nexus. ([see relevant page](#))
- The functions that received the largest FDI inflows, out of 16,084 total projects between 2003 and 2016, are sales, marketing, and support: 6,198, manufacturing: 2,725, business services: 2,485, logistics, distribution, and transport: 1,399, and headquarters: 1,078. ([see relevant page](#)).
- The functions that received the fewest FDI inflows are extraction: 7—a function only possible for industry C20: chemical extraction—electricity: 9, shared services centers: 35, recycling: 41, and customer contact centers: 56. ([see relevant page](#)).
- The publishing industry received the most FDIs with 2,274 total, following by computer and electronic manufacturing: 1,625, the manufacture of machinery and equipment: 1,196, computer programming and information services: 883, and then legal/accounting and consultancy activities: 868. ([see relevant page](#)).
- The Fewest FDIs were received by industries of trade and repair of vehicles: 5, printing of recorded media: 26, courier activities: 42, wholesale trade: 55, and water transport: 79. ([see relevant page](#))

- Innovation patterns have generally become more concentrated over time with earlier periods (1994-2000) typically showing more dispersed distributions and recent periods (2012-2016) showing more similarity across different types of innovation performance over time. ([see relevant page](#))
- General innovation is a strong indicator of all types of innovation, with 83% correlation with product and organization innovation (the strongest correlation) and 73% correlation with process innovation. The weakest correlation is between process and organization innovation at 67%, which is still quite high. ([see relevant page](#))
- The period 1994-2004 shows a leftward shift in innovation performance peaks, meaning a greater concentration of industries containing a smaller percentage of general innovators. The latter years, 4, 5, and 6, corresponding to the years 2005-2016, display much smoother innovation patterns, with shorter peaks, especially along the lower innovation rates (below ~40%), confirming what was shown in figure 8, which is a flatter, more spread-out distribution, suggesting innovation became more varied across firms over time, with less concentration around specific adoption rates. ([see relevant page](#))
- The most generally innovative country is Germany with very few industries containing less than 50% of firms introducing general innovations on average over time. Italy and Spain seems to be the least innovative countries, with France and the Netherlands landing between these two extremes. ([see relevant page](#))
- Across all innovation forms, the industries with the highest aggregate propensity for innovation in Europe between 1994 and 2016 are SB: Science Based industries, and the ones with the lowest capacity for innovation are SD: Supplier Dominated industries. SII and SS industries record similar innovation performances across all forms of innovation capacity with the exception of process innovation, which in general is the category that shows the lowest innovation rates in Europe, perhaps because of being tied to commonly outsourced production functions where Europe does not typically specialize. See next chapter ([see relevant page](#))

These findings outline the general patterns in FDI inflow and innovation propensities by 38 European industries across Germany, Spain, France, Italy, and the Netherlands, 5 countries that collectively account for over 70% of the European economy. The following chapters, using the methodology outlined in [section 2.1](#) above and the merged FDI-SID dataset, show a strong association exists between innovativeness and the functional position of industries in GVCs, using inward FDI-based Balassa (1965) indices of functional specialization, which is reported and discussed in the following chapter.

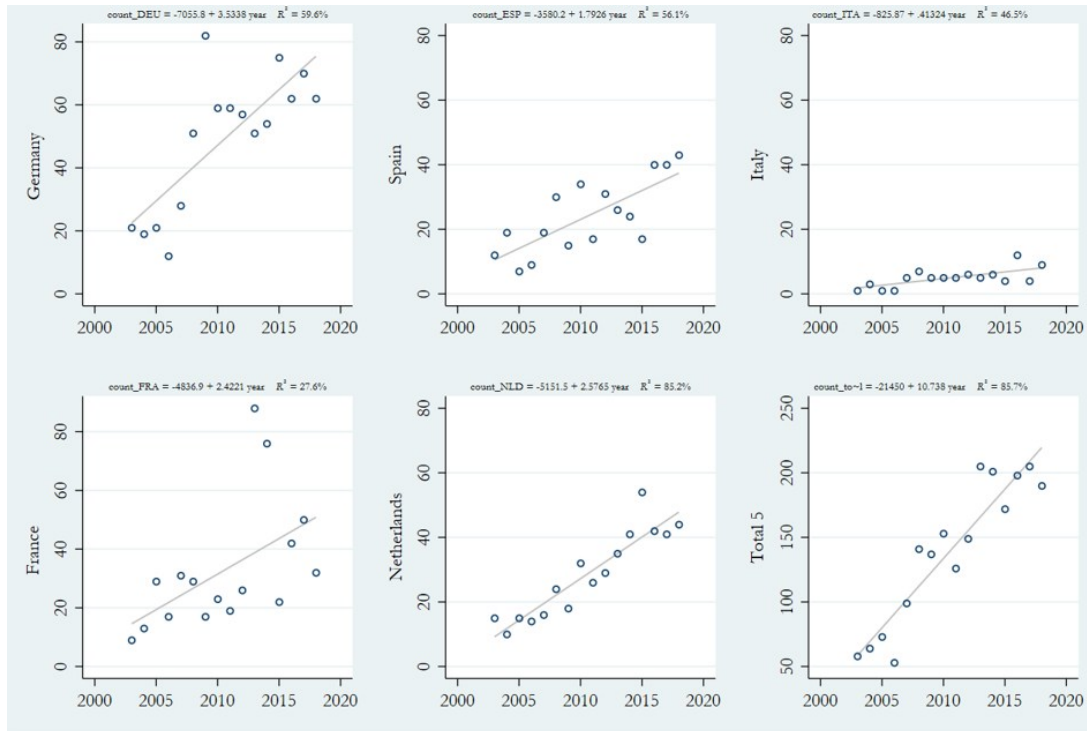
Chapter 2 References

- Altenburg, T. (2006) Governance Patterns in Value Chains and their Development Impact. *The European Journal of Development Research*, 18(4), 498–521
- Altenburg, T., Schmitz, H., & Stamm, A. (2008). Breakthrough? China's and India's Transition from Production to Innovation. *World development*, 36(2), 325-344
- Ambos, B., Brandl, K., Perri, A., & Scalera, V. G. (2021). The Nature of Innovation in Global Value Chains. *Journal of World Business*, 56
- Brandt, L., & Thun, E. (2011) Going Mobile in China: Shifting Value Chains and Upgrading in the Mobile Telecom Sector. *International Journal of Technological Learning, Innovation and Development*, 4, 148–180
- Cafaggi, F et al. (2012). Accessing the Global Value Chain in a Changing Institutional Environment: Comparing Aeronautics and Coffee, IDB Working Paper Series, No. IDB-WP-370, Inter-American Development Bank (IDB), Washington, DC, <https://hdl.handle.net/11319/4250>
- Comotti, S., Crescenzi, R., & Iammarino, S. (2020). Foreign Direct Investment, Global Value Chains and Regional Economic Development in Europe. *Publications Office of the European Union*
- Coveri, A. & Zanfei, A. (2022). Functional Division of Labour and Value Capture in Global Value Chains: A New Empirical Assessment Based on FDI Data. *Review of International Political Economy*, 1-28
- Coveri, A., Pagliarunga, E., & Zanfei, A. (2024). Functional Specialization & Upgrading in European Regions: New Insight from FDI Data. Working Paper series 2401, 1-27, University of Urbino Carlo Bo, Department of Economics, Society & Politics
- De Marchi, V., Di Maria, E., Golini, R., & Perri, A. (2020). Nurturing International Business Research Through Global Value Chains Literature: A Review and Discussion of Future Research Opportunities. *International Business Review*, 29, 1-16
- Fagerberg, J. & Sapprasert, K. (2011). National Innovation Systems: the Emergence of a New Approach. *Science and Public Policy*, 38(9), 669-679
- Fagerberg, J., Srholec, M., & Verspagen, B. (2010) Innovation and Economic Development. In Bronwyn H. Hall and Rosenberg N. (eds) *Handbook of the Economics of Innovation*, 2, 833–872
- Farole, T. & Winkler, D. (2014). Making Foreign Direct Investment Work for Sub-Saharan Africa Local Spillovers and Competitiveness in Global Value Chains. *Direction in Development: Trade*. Washington, DC: World Bank
- Ferriani, S., Lipparini, A., & Lorenzoni, G. (2014). From Core to Periphery and Back: A Study on the Deliberate Shaping of Knowledge Flows and Interfirm Dyads and Networks. *Strategic Management Journal*, 35, 578-595
- Fu, X., Zanello, G., Essegbey, G.O., Hou, J., & Mohnen, P. (2014) *Innovation in Low Income Countries: A Survey Report*. Oxford: Department of International Development
- Kadariusman, Y. (2012) Knowledge Acquisition: Lessons from Local and Global Interaction in the Indonesian Consumer Electronics Sector. *Institutions and Economies*, 4(2), 65–100
- Kadariusman, Y. B. (2011). *Global Value Chains and Technological Capabilities: Analysing the Dynamics of Indonesia's Garments and Electronics Manufacturers*. The University of Manchester (United Kingdom)
- Kim, L. (1997). *Imitation to Innovation. The Dynamics of Korea's Technological Learning*. Harvard Business School Press
- Kokko, A., Tansini, R., & Zejan, M. C. (1996). *Local Technological Capability and Productivity*

- Spillovers from FDI in the Uruguayan Manufacturing Sector. *The Journal of Development Studies*, 32(4), 602-611
- Lema, R., Berger, A., & Schmitz, H. (2013). China's Impact on the Global Wind Power Industry. *Journal of Current Chinese Affairs*, 42(1), 37-69
- Melendez, M., & Uribe, M. J. (2012) International Product Fragmentation and the Insertion of Latin America and the Caribbean in Global Production Networks: Colombian Case Studies. Washington, DC: Inter-American Development Bank Working Paper No. IDB-WP-374
- Meyer, K. E., & Sinani, E. (2002). Identifying Spillovers of Technology Transfer from FDI: the Case of Estonia. Obtained from <https://research-api.cbs.dk/ws/portalfiles/portal/59008864/7057.pdf>
- Padilla-Perez, R. (ed). (2014). Strengthening Value Chains as an Industrial Policy Instrument. Methodology and experience of ECLAC in Central America. Santiago: Economic Commission for Latin America and the Caribbean (ECLAC)
- Pianta, M, Coveri, A. & Reljic, J. (2021). The Sectoral Innovation Database 1994-2016 Methodological Notes. UniUrb Working Paper (WP) series in Economics, Mathematics, and Statistics (EMS). WP-EMS # 2021/1. ISSN 1974-4110 (online edition); 1594-7645 (print edition)
- Pietrobelli, C. & Rabellotti, R. (2011). Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? *World Development*, 39, 1261-1269
- Schmitz, H. (2006) Learning and Earning in Global Garment and Footwear Chains. *The European Journal of Development Research*, 18(4), 546-571
- Stollinger, R. (2021). Testing the Smile Curve: Functional Specialisation and Value Creation in GVCs. *Structural Change and Economic Dynamics*, 56, 93-116. <https://doi.org/10.1016/j.strueco.2020.10.002>
- Sturgeon, T.J., & Kawakami, M. (2011) Global Value Chains in the Electronics Industry: Characteristics, Crisis, and Upgrading Opportunities for Firms from Developing Countries. *International Journal of Technological Learning, Innovation and Development*, 4(1/2/3), 120-147

Chapter 2 Appendix

Item A. Number of Inwards FDI in Headquarters Functions Over time



Item B. Number of Inwards FDI in Logistics Functions Over Time



Chapter 3 | Innovation Performance and Functional Specialization of EU Industries: New Evidence from the SID

3.0 | Executive Summary and Chapter Roadmap

The growing centrality of intangible assets within global value chains (GVCs) has fundamentally reconfigured the distribution of gains from trade and investment, shifting the unit of analysis from products to functions. Within this framework, functional specialization has emerged as a decisive determinant of value capture, with mounting empirical evidence showing that economic geographies concentrated on pre- and post- production functions systematically secure higher returns than those specialized in production activities. However, the majority of these studies have focused on value capture in terms of monetary profit. This chapter asks if the same pattern is true for innovation performance. Specifically, are functions also hierarchical in terms of innovation, with intangible-based functions associated with higher innovation performance than their tangible counterparts? What about the role of functional diversity? Is it also associated with higher Innovation Performance?

This chapter posits that a mechanism underpinning the nexus between intangible assets and profitability partly lies in innovation capacity as an intermediate catalyst (see [section 1.6.1](#): “Intangibles and the Changing Purpose of Innovation”), and it therefore examines this relationship in depth. Drawing on FDI Markets data in combination with the Sectoral Innovation Database (SID), the study constructs a dataset of 38 industries across five European economies—Germany, Spain, France, Italy, and the Netherlands—between 2003 and 2016.

Quantitative analysis demonstrates that (1) specialization in intangible-intensive functions is consistently associated with superior innovation outcomes compared to tangible-intensive ones, with the effect amplified in post-production functions as GVC participation deepens; (2) diversification strongly correlates with innovation across all dimensions, particularly product innovation, even when controlling for the number of FDI projects. Simple regressions formalize the relationship between functional diversification and innovation performance showing that even when accounting for country specific differences, industry specific innovation expenditure rates, and number of inward FDIs, functional diversification is statistically and substantially significant, **but only in the service sector, and not manufacturing**.

Section 3.1 shows how leveraging rich industry-level datasets—like the Sectoral Innovation Database (SID)—enables analysis of how patterns of functional specialization relate to different forms of innovation and value creation across various European industries. Section 3.2 presents the functional specialization index (FSI) indicator used in this and the coming chapter. In doing so, data is presented in 3 different layers of aggregation: functional specialization by individual (17) functions as tagged in FDI-M; FSI by 5 narrow functional groups as per Strollinger (2021); and the most traditional division of preproduction, production, and postproduction. Data patterns are briefly presented by country, showing the specialization of each country and some key industries in a cross-sectional format. This chapter does not look at data over time—panel structure—but rather as a cross section.

Sections 3.3 and 3.4 present the results related to functional specialization and diversification—respectively. These results indicate that the Smile curve hypothesis can be extended from specialization-value nexus only to also specialization-innovation nexus. That is, industries specialized in preproduction and postproduction functions command consistently higher innovation rates than industries specialized in production functions.

Moreover, it is shown that functional diversification is linked to higher product and process but not organization innovation performance in the services sector **only**. Regressions results suggest that manufacturing innovation is mostly driven by standard efficiency- and productivity- based explainers. This is consistent with the 'low road' and 'cost competitive' strategies often adopted by firms specialized in production, which, relatively, the manufacturing sector is specialized in.

These findings allow us to accept the hypotheses:

$H^{A1} \rightarrow$

PRE- & POST- ARE LINKED TO HIGHER INNOVATION RATES THAN PRODUCTION- SPECIALIZATIONS

$H^{B1} \rightarrow$

MORE DIVERSIFIED INDUSTRIES CAPTURE HIGHER INNOVATION RATES

[ACCEPTED WITH CAVEAT: SERVICES BUT NOT MANUFACTURING]

3.1 | Introduction: Measuring Functional Specialization, Innovation, & Controls

The present research examines the specialization-innovation nexus by employing the Sectoral Innovation Database (SID), developed by Pianta, Coveri, and Reljic (2021). The SID represents a comprehensive and harmonized dataset on innovation activities across Europe, built on the foundation of the European Community Innovation Survey (CIS). Covering 21 manufacturing and 17 service sectors across 5 EU countries over more than two decades, SID offers consistent, longitudinal, and internationally comparable measures of innovation activities. Its linkage to national accounts ensures macroeconomic consistency, while its reliance on harmonized CIS instruments guarantees comparability across countries. This makes SID uniquely suited for cross-national, industry-level analyses of innovation in relation to functional specialization.

Crucially, the SID moves beyond narrow proxies for innovation such as R&D expenditures or patent counts. This is critical as these measures (see Chapter 1) often conflict between intangibles and innovation, the two variables we are relating to each other. Instead, the SID captures product, process, and organizational innovation propensities of industries. As detailed with the aid of various stylized summary statistics in the previous chapter, 2, product innovations, often concentrated in science-based industries, alter competitive dynamics through new goods and services, capturing a form of innovation where ‘technology is an outcome’; process innovations transform productivity by improving production techniques; organizational innovations, pervasive across services and manufacturing alike, restructure firms’ internal and external coordination mechanisms, enabling more effective exploitation of new business models and knowledge assets.

While the bifurcation of innovation into product, process, and organizational is not new, nor does it neatly align with the reality of modern economic technologies as simplistically as just described (as is the point of Chapter 1), the *meso* level discrimination of innovation types allows for a more detailed understanding of the effects of specialization on the capacity of a cluster of firms to continuously innovate. Additionally, while being survey-based has some known drawbacks, the Community Innovation Survey (CIS)’s self-reported *introduced innovations* variables do allow us to bypass problems related to definitional murkiness and subjectivity concerning innovation discussed in the first chapter.

The SID also incorporates data relating to industry size, industry classification by Pavitt taxonomy, number employees & firms, as well as other controls, and data about expenditure on tangible and intangible assets. Some of these variables are incorporated in the regressions in [section 3.4](#), such as the variables concerning expenditure on innovation by industry and number of employees in an industry. By encompassing all these variables and more than the usual dimensions of innovation, SID reflects the complex reality of innovation systems, aligning empirical measurement with the theoretical recognition of ‘open’ and ‘interactive’ models of learning in firm capabilities and GVC (Malerba, 2002; Evangelista & Vezzani, 2010; Cohendet & Simon, 2017).

The analytical strength of SID is further enhanced when combined with an industry-level approach. As Pavitt (1984) argued, industries are not homogeneous with respect to their innovation dynamics; sectoral regimes determine the opportunities, incentives, and modalities of innovation. Pharmaceutical and IT industries are science-based and heavily R&D-intensive; mechanical engineering and automotive industries often rely on specialized supplier and scale-intensive patterns; while textiles, construction, and many service sector actors are supplier-dominated. **Aggregating these divergent patterns at the national level risks conflating industry effects with functional specialization effects.** By disaggregating to the industry level, the present study effectively controls for industry fixed

effects, ensuring that observed relationships between functional specialization and innovation are not artefacts of sectoral composition.

At the same time, the comparative European design of this study introduces natural controls for heterogeneity across national innovation systems (see NSI discussion in chapter 1). The European Union provides a shared institutional environment—common competition law, harmonized intellectual property regimes, EU-level research funding programs such as Horizon Europe—while preserving meaningful variation in industrial structures and policy traditions (Archibugi & Filippetti, 2011; Veugelers, 2016). By focusing on five major European economies that together account for roughly three-quarters of EU GDP and innovation activity, the study leverages both similarity and diversity: the similarity ensures comparability and controls for confounding systemic differences, while the diversity provides variation necessary for inference. This makes Europe an ideal laboratory for examining functional specialization–innovation linkages.

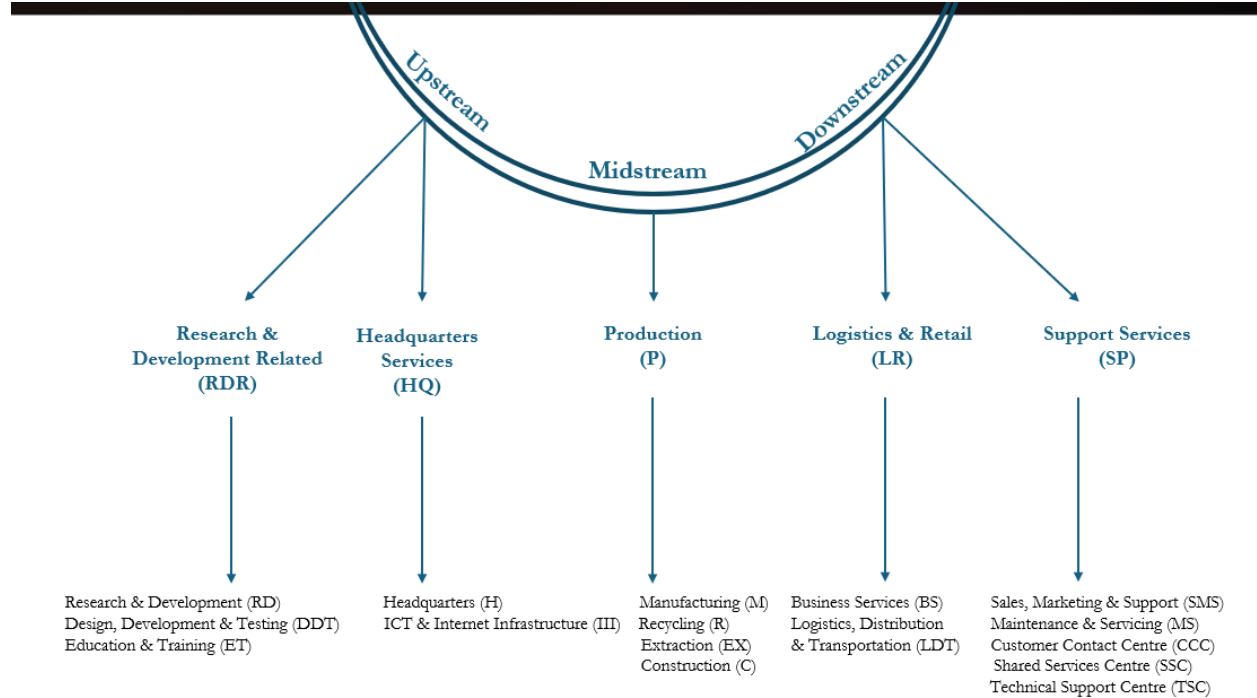
Through this design, the study generates evidence that directly tests the proposition at the heart of the functional specialization literature: that innovation is involved in underpinning value asymmetries in GVCs. By linking industry-level functional specialization profiles to multiple types of innovation from the SID, **the analysis assesses whether specialization in intangible-intensive functions indeed translates into higher product, process, and organizational innovation, and whether diversification across functions enhances innovation resilience. It thus builds upon and extends the arguments and findings of Coveri and Zanfei (2022, 2023), providing a theoretically grounded assessment.**

The relevance of this inquiry extends beyond academic debates. The disruptions of the COVID-19 pandemic exposed the vulnerabilities of hyper-specialized GVCs, particularly in medical equipment and pharmaceuticals (Javorcik, 2020). The semiconductor shortage that paralyzed European automotive industries highlighted the risks of relegating critical functions outside of Europe. At the same time, the EU’s “twin transitions” of digitalization and sustainability demand a robust and resilient innovation base across industries. Understanding how functional specialization and diversification shape innovation capacity is thus vital for informing industrial strategies that balance efficiency with resilience. This will be further elaborated in chapter 5, the conclusion, with reference to specific EU policies and initiatives for innovation and functional sovereignty.

3.2 | EU Functional Specialization Profiles—FSP (FDI Data)

Data used in this study (particularly this chapter and the next) are available in three levels of aggregation by function. The **first** consists of 17 economic activities with which FDI Markets tags inward FDI projects; the **second** consists of 5 “narrow” groupings of these functions according to Stollinger (2021); and the **third** groups all functions by broad category—i.e. smile curve position (the latter is only relevant for the next chapter, 4):

Figure 1. Three Layers of Aggregation of Economic Functions



For each layer of aggregation, the same formula was applied to compute a Balassa (1965) relative functional specialization index (FSI). The formula to compute this index is based on the number of inward FDIs (not their monetary value)—that is, the number of FDIs entering an industry in a given function. This *count* is derived from the FDI Markets database, which includes data on almost 30,000 FDI projects entering Germany, Spain, France, Italy, and the Netherlands between 2003 and 2016.

The FSI index can be understood as denoting the share of a share. Specifically, it denotes

- (1) the fraction of FDIs in function f relative to the total FDIs for all functions in an industry i for a country c
as a share of
- (2) the fraction of FDIs in function f across all countries relative to the total FDIs for all functions in an industry i

This means the FSI measures the distribution of FDIs across functions at the country and aggregate level, after which relates them to each other to obtain a Balassa (1965) index, wherein a value higher than 1 means that an industry is specialized in a given function relative to the same industry-function pair in all other countries. A score below 1 means it is relatively less specialized. The formula for calculating FSI is presented below:

Step 1: Country Level Functional Specialization Index (FSI1)

$$FSI1_{c,i,f} = \frac{FDI_{c,i,f}}{\sum_{f=1}^n FDI_{c,i,f}}$$

Where:

c = country; i = industry; f = function; and

$FSI1_{c,i,f}$ is the fraction of FDIs in function f relative to the total FDIs for all functions in an industry i for a county c

Step 2: Aggregate Functional Specialization (FSI5)

$$FSI5_{i,f} = \frac{\sum_{c=1}^m FDI_{c,i,f}}{\sum_{c=1}^m \sum_{f=1}^n FDI_{c,i,f}}$$

Where:

m = total number of countries; n = total number of functions; and

$FSI5_{i,f}$ is the fraction of FDIs in function f across all countries relative to the total FDIs for all functions in an industry i

Step 3: Functional Specialization Index (FSI)

$$FSIx_{c,i,f} = \frac{FSI1_{c,i,f}}{FSI5_{i,f}}$$

Where:

$FSIx_{c,i,f}$ is the specialization of industry i of country c in function f relative to the aggregate specialization across all countries

3.2.1 | The Limits and Merits of the FSI Indicator: How to Interpret it?

The FDI-based measure of functional specialization has strengths and limitations that must be acknowledged upfront to guide our interpretation of what it is and, perhaps more importantly, what it is not.

Strength: Reliability

The capital investment figures in FDI Markets are almost exclusively estimated, with no transparent criteria for how those estimates are generated. This makes monetary value less trustworthy than project frequency. Project counts are observed facts; monetary values are educated guesses.

Limitation: Project counts ignore monetary value

The number of FDI projects does not capture the magnitude of capital invested. Larger investments plausibly generate stronger direct and indirect effects, including spillovers, on host economies. **If our goal were to measure the causal impact of specific FDI projects on industry outcomes, monetary value would be critical. However, that is not what this study does. The FSI index is not a measure of FDI effects; it is a diagnostic indicator of functional specialization.** An FSI above 1 does not mean a region became specialized because of these particular FDIs that went into the calculation. Rather, an FSI of 1 means that, as evidenced by the distribution of FDIs, the region *is* specialized. The FDI count reveals existing specialization; it does not claim to explain how that specialization emerged or the effect on innovation of the process of attaining that specialization (see related strength below: “theoretical appropriateness”).

Strength: Theoretical appropriateness

Firms' decisions about where to locate specific functions are often relatively independent of the amount of capital invested. What matters for functional specialization is the location decision itself. Crescenzi et al. (2016) explicitly argue that the number of investment decisions in a given geographical destination is a more appropriate unit of analysis than project value, precisely because these decisions are broadly independent of capital invested:

It is worth stressing that the number of investment projects is a more appropriate unit of analysis than their value when looking at the location strategies of multinationals because the choice of a specific country is largely independent from the amount of capital invested (Amighini, Cozza, Rabellotti, & Sanfilippo, 2014; Sutherland & Anderson, 2014). Moreover, the investment value varies widely across sectors, with resource-intensive sectors showing higher average investment value than consumer goods sectors or services. This is the main reason why several empirical studies have chosen the number of deals (and not the investment value) as their unit of analysis (among others, see Castellani & Pieri, 2013; Crescenzi et al., 2014; Ramasamy, Yeung, & Laforet, 2012). (Crescenzi et al, 2016: 651)

In other words, the volume of inward FDI tells us the industry we are looking at is likely good at a particular function if most of these FDIs is going into that function. As such, the number of projects is an indicator of specialization, though the monetary value of those projects would be a better indicator of the impact of the projects themselves on the host economy.

Limitation: Functional heterogeneity in project value

Monetary value varies systematically by function. Upstream activities like R&D and headquarters command vastly larger capital per project than downstream functions like sales, marketing, or support. A single R&D project may equal dozens of support projects in dollar terms. This makes cross-functional comparisons without monetary value difficult. Again, this is if we compare the ‘effects’ of these specific FDIs, which is not the goal; rather, it is the revealed specializations denoted by the ability to attract FDIs that is of interest.

For these reasons, a substantial literature using FDI Markets has consistently relied on project counts rather than monetary value, as is denoted in the block quote above from Crescenzi et al. (2016). In sum, while monetary value would be ideal for capturing investment magnitude, its estimated nature makes it unreliable. More critically, for measuring functional specialization, project counts are theoretically superior: they capture where firms choose to locate functions, which is precisely what specialization measures.

3.2.2 | Heatplots: Individual Functions Specialization by Industries

Given a dataset of 186 observations (38 national industries multiplied by 5 countries minus 4 industries who received zero FDIs across all functions), an equal number of Functional Specialization Index (FSI) scores are presented below in different manners corresponding to the three levels of aggregation. This is because of two main reasons: first, different aggregations act as robustness checks when a degree of granularity is needed but suffers from insufficient variation or observations; and second, because the idea of functional profiles forces us to think simultaneously in terms of different aggregations of functional specialization as each sheds different light on different dynamics within the specialization-innovation nexus.

The pages below contain five heat plot grids. Each grid has 646 points of intersection reflecting the two dimensions of analysis: 38 industries & 17 functions. **A blank intersection** (eg. RD & C10-C12 in the first heat plot: Germany) signifies that no FDIs were received by Germany’s C10-C12 industry to perform R&D functions. The darker the colored rectangle at an intersection point, the less specialized that country’s industry is in the corresponding function. Two colors are particularly important, and these are the two most prevalent. **A dark blue color rectangle denotes a relative lack of specialization of country c ’s industry i in function f . This means that industry’s functional specialization score in a given function is between 0 and 1. A light brown rectangle denotes the relative specialization of country c ’s industry i in function f . This means that industry i received a score between 1 and 2.** For example, Germany’s M72 is specialized in Education & Training (ET) but not in Design, Development, & Testing (DDT) with respect to the average specialization of all 5 countries’ M72 industries in ET and DDT.

Values above 2 denote varying intensities of specialization. For example, Italy has 4 values above 20, the highest in the entire sample of 3000+ individual FSI scores. For example, a score of 26.5 sees Italy specialize in Design, Development, & Testing (DDT) in M71: Architectural & Engineering Activities (M71.1); Technical Testing and Analysis (M71.2), which is a high tech, Specialized Supplier (SS) service industry. Given Italy’s singular architectural past monuments, buildings, and man-made landscapes, it is certainly understandable why M71 is receiving almost only FDIs in DDT.

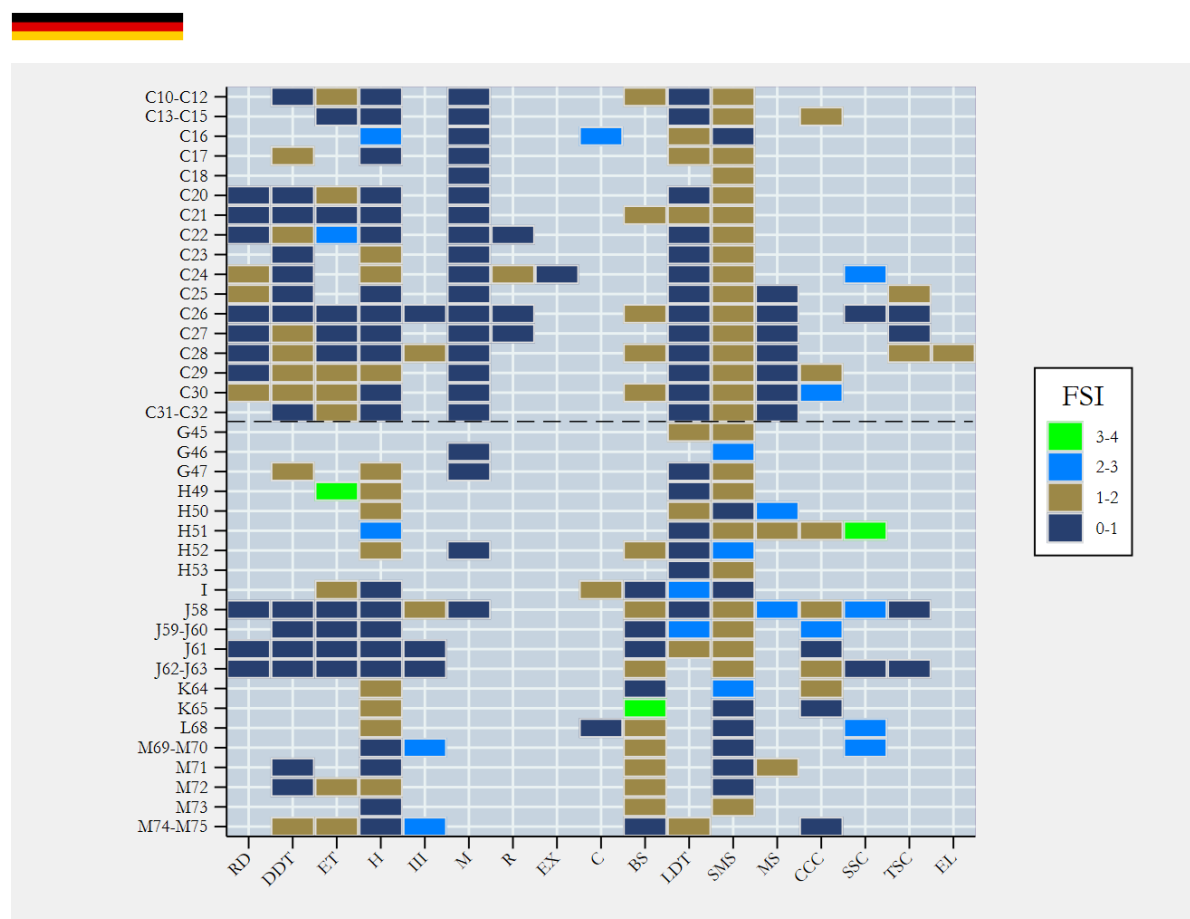
However, it is important to note that the total FDIs that yielded this hyper specialization score is just 4. The reason the specialization score is 26.5 has to do with the fact that neither Spain, France, nor the Netherlands received any FDIs in M71 to perform DDT functions, and Germany received just 1

FDI such that almost ALL (4 out of 5) the design, development, and testing in architecture and civil engineering is performed in Italy. As is noted shortly, the interpretation of 4 FDIs is tricky, as while that number seems small, their position as upstream FDIs often connotes with high value FDIs (large monetary value and longer projects).

The other 3 white coloured rectangles are based off 1 FDI entering Italy and 0 entering the other 4 countries. As such, these extreme values tend to represent statistical anomalies that, if interpreted with care, could produce some little value at the industry level, **but should and will, for the most part, be only interpreted at the country level, which means aggregating across industry.** In general, Italy (and to a slightly lesser extend the Netherlands) presents a contentious case as, having received so few FDIs—7% of the total sample (10% in the case of NL)—many single-function specialization scores are cases where high values are based on few FDIs total entering the industry.

Given this statistical challenge, most major analysis will be conducted at higher levels of aggregation of functions or by imposing a lower bound cut off for number of FDIs, namely 50, (see following subsections). That said, it is still important to briefly present and discuss specialization patterns by individual functions without any cut offs, to understand the most granular base for the upcoming arguments →

Figure 2. Functional Specialization & Diversification Heatplot, Germany, 2003-2016 Averages



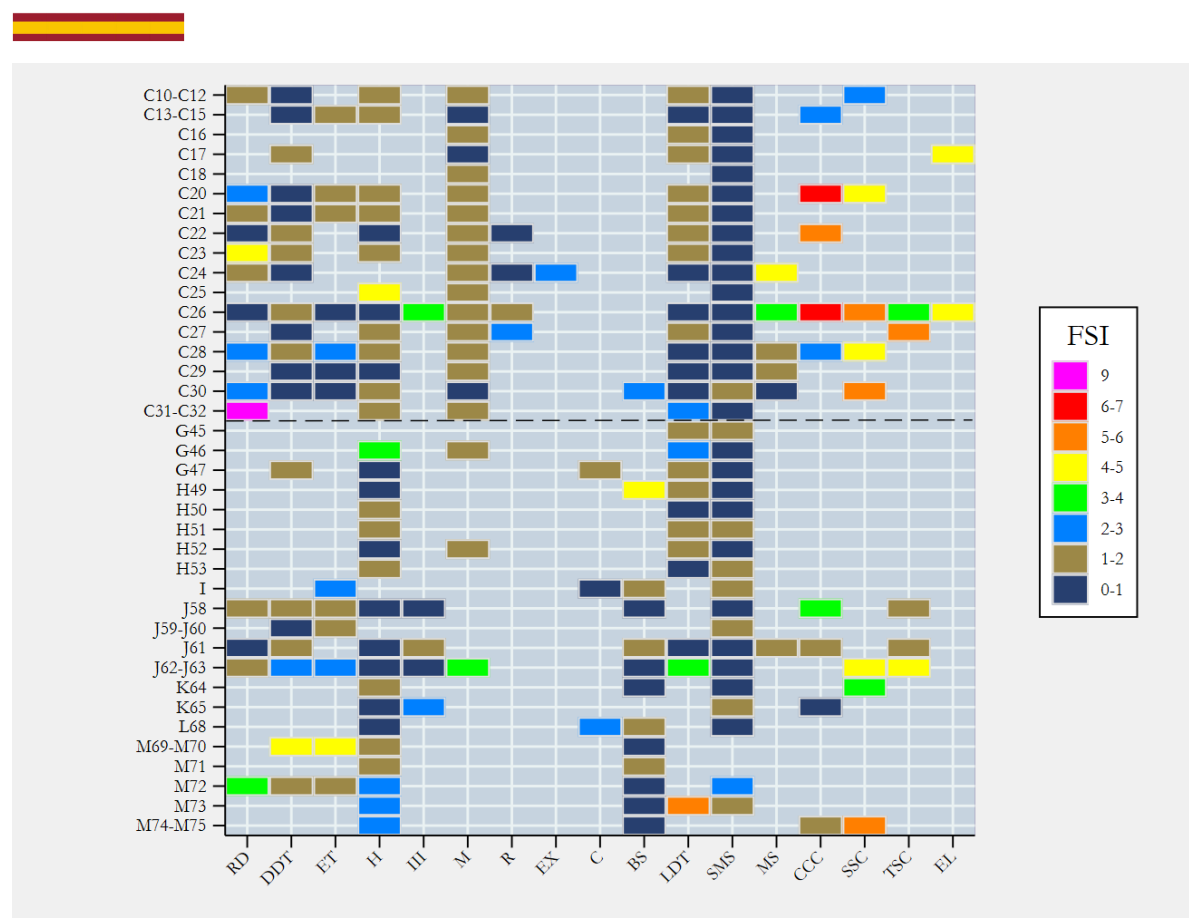
The heat plot illustrates the cross-sectional distribution of functional specializations across various industries in **Germany**, with 2003-2016 aggregated data. It reveals a relatively uncomplex landscape

where most industries exhibit low to moderate specialization in specific economic functions, with only a few instances of high specialization. This is evident in sectors such as land transport (H49), air transport (H51), and insurance & pension funding (K65), where the Functional Specialization of Industries (FSI) index reaches its highest levels of 3-4 in Education & Training (ET), Shared Services Center (SSC), and Business Service (BS) functions, respectively. However, most of the plot is dominated by **0-1**: no specialization and **1-2**: relative specialization FSI, indicating a more generalized functional distribution rather than concentrated specialization.

It is notable that German industries are relatively not specialized in almost any midstream function, with small exceptions such as construction functions in C16. Conversely, there is some moderate specialization in the preproduction functions concerned with high tech manufacturing of vehicles, transport equipment, and machinery. The greatest specialization pattern, however, relates to SMS functions, where specialization across industries seems to be the national norm.

The relatively sparse presence of strong specialization (green) alongside the predominance of lower specialization levels (brown) suggests that **FDI inflows in Germany are more evenly dispersed across functional tasks rather than concentrated in a narrow set of specialized functions**. This could reflect a strategy of diversified functional capacity rather than deep specialization in a limited set of high-value tasks. The presence of moderate specialization in design, headquarters, logistics, and professional services aligns with Germany's established role as a hub for advanced high-tech design and technical expertise.

Figure 3. Functional Specialization & Diversification Heatplot, Spain, 2003-2016 Averages



Perhaps the most notable part of Germany's FSP plot concerns the relative abundance (absence) of dark blue (light brown) on the left side upstream functions and *vice-versa* for the right-side downstream functions. This point becomes increasingly important as this chapter progresses.

The heat plot for functional specialization across industries in **Spain** reveals a more heterogeneous pattern compared to Germany, with notable instances of strong specialization. High FSI values are more frequent and concentrated in specific industries and functions. First, there is a striking absence of **dark blue** and presence of **light brown** shades, indicating that industries in Spain display concentrated specializations relative to Germany and the rest of the countries. In fact, apart from SMS—and to a lesser extent LDT & BS— functions, it seems the general rule that when FDIs enter Spain they enter specialized industries, or they do not enter at all.

Second, there is, however, no pattern of specialization by functional group. In other words, industries exhibit multiple simultaneous high-magnitude specializations. Notable examples include manufacture of chemicals (C20), which shows specialization in all but one pre-production functions, manufacturing, three post-production functions, including specialization in customer contact and shared service center functions; and manufacture of computer and electronic products (C26), registering functional specialization in design, infrastructure, manufacturing, recycling, and all but 2 post-production functions. In fact, C26 stands out as the most specialized industry, showing multiple times the average specialization score in MS, CCC, SSC, & TSC. Third, Spain's most specialized functions across all industries are manufacturing and headquarter functions.

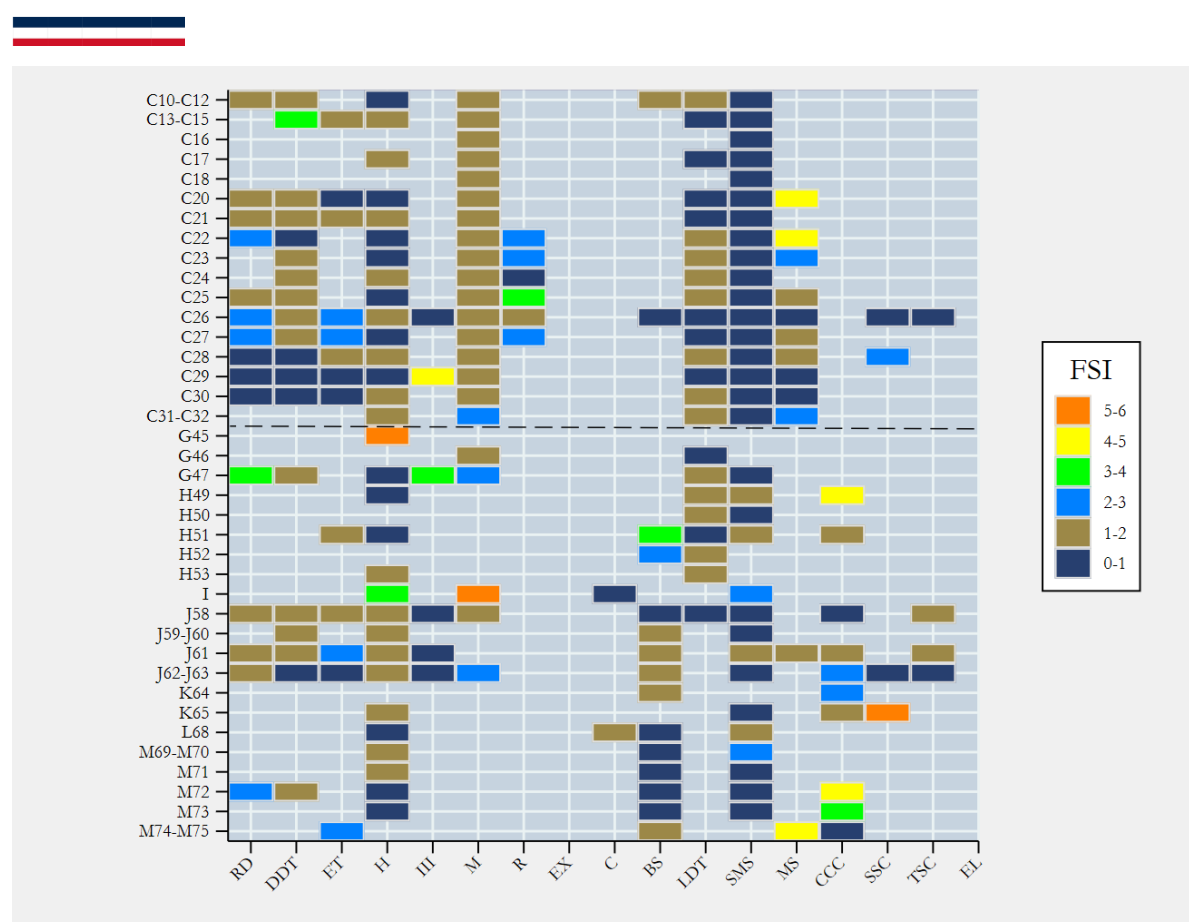
In all, the data suggests a dual structure where certain industries pursue specialized functional strategies while others maintain a more generalized distribution across tasks. The broader presence of higher FSI values in Spain relative to Germany, could reflect a more polarized functional landscape, where some industries concentrate heavily on a few tasks while others diversify evenly.

The heat plot for functional specialization across industries in **France** reveals something in between the patterns of Germany and Spain. Low FSI values are concentrated. Specifically, the dark blue rectangles denoting a lack of relative functional specialization are concentrated vertically in SMS functions, and horizontally in the manufacturing of machinery, motor vehicles, and other transport equipment industries. Outside of this, France shows relative specializations. Most notably, France shows specialization in manufacturing in every single manufacturing industry, all of which received FDIs (no blank intersections). In fact, the few services industries that received FDIs in the manufacturing function are all relatively specialized as well with a few instances of hyper specialization.

Like Spain, there is no pattern of dominant specialization—i.e. industries exhibit multiple high-magnitude specializations (however, fewer than in Spain). HQ and LDT functions exhibit the second largest specializations across industries after manufacturing, with upstream functions displaying more specialization in general than downstream functions.

The most diversified industry seems to be J61, Telecommunications, a Science-Based high-tech service industry. All in all, France demonstrates a close resemblance to Germany than any other country in terms of its overall specialization strategy, with a few traits like Spain such as the upstream concentration of specialization

Figure 4. Functional Specialization & Diversification Heatplot, France, 2003-2016 Averages

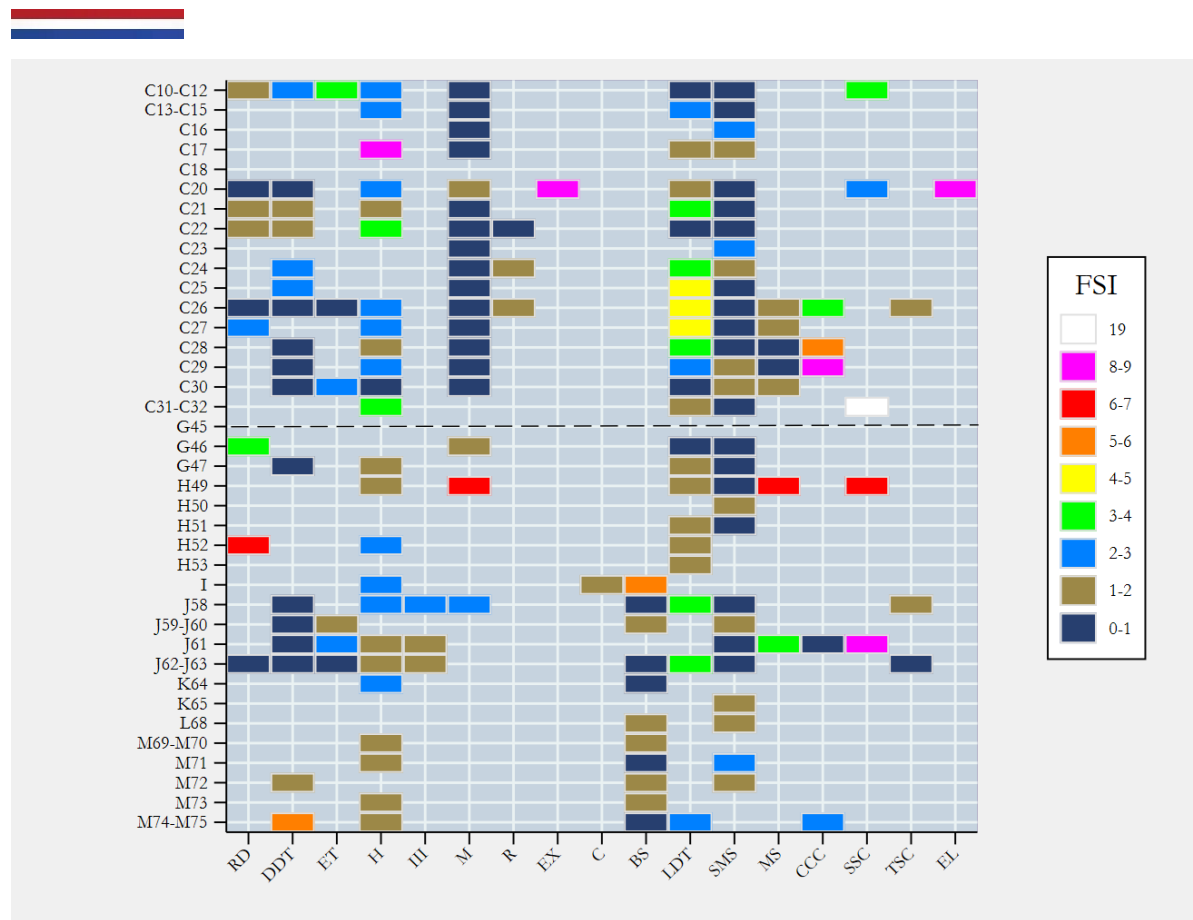


The heat plot for functional specialization across industries in the Netherlands reveals 4 main patterns:

First, **the Netherlands'** consistent and steep increase in number of FDIs in HQ functions is evidenced in the by-industry analysis here. Of the 38 industries, only 14 did not receive HQ FDIs, while 24 did. Of those 24, **only 1 is not specialized in HQ functions**, relative to the same industries in other countries (C30). Of the remaining 23, 10 display *regular* levels of specialization (1-2), while 13 displays various higher magnitudes of specialization (brighter colors). Second, a similar pattern, but to a lesser extent, can be observed in LDT, Holland's second largest functional specialization across all industries

Third, the Netherlands joins Germany in almost entirely lacking specializations in manufacturing and the other midstream functions of recycling and construction. This is in line with common knowledge concerning the cost of manufacturing in both those countries, and the need for outsourcing that function. Fourth, as is the case in Italy, there is a particular and noticeable abundance of bright coloured, particularly light blue rectangles, and this is even more particularly true in the case of upstream functions in high tech manufacturing sector. However, dissimilar to Italy is the fact that there tends to be more diversification of functional specializations across industries.

Figure 5. Functional Specialization & Diversification Heatplot, Netherlands, 2003-2016 Averages

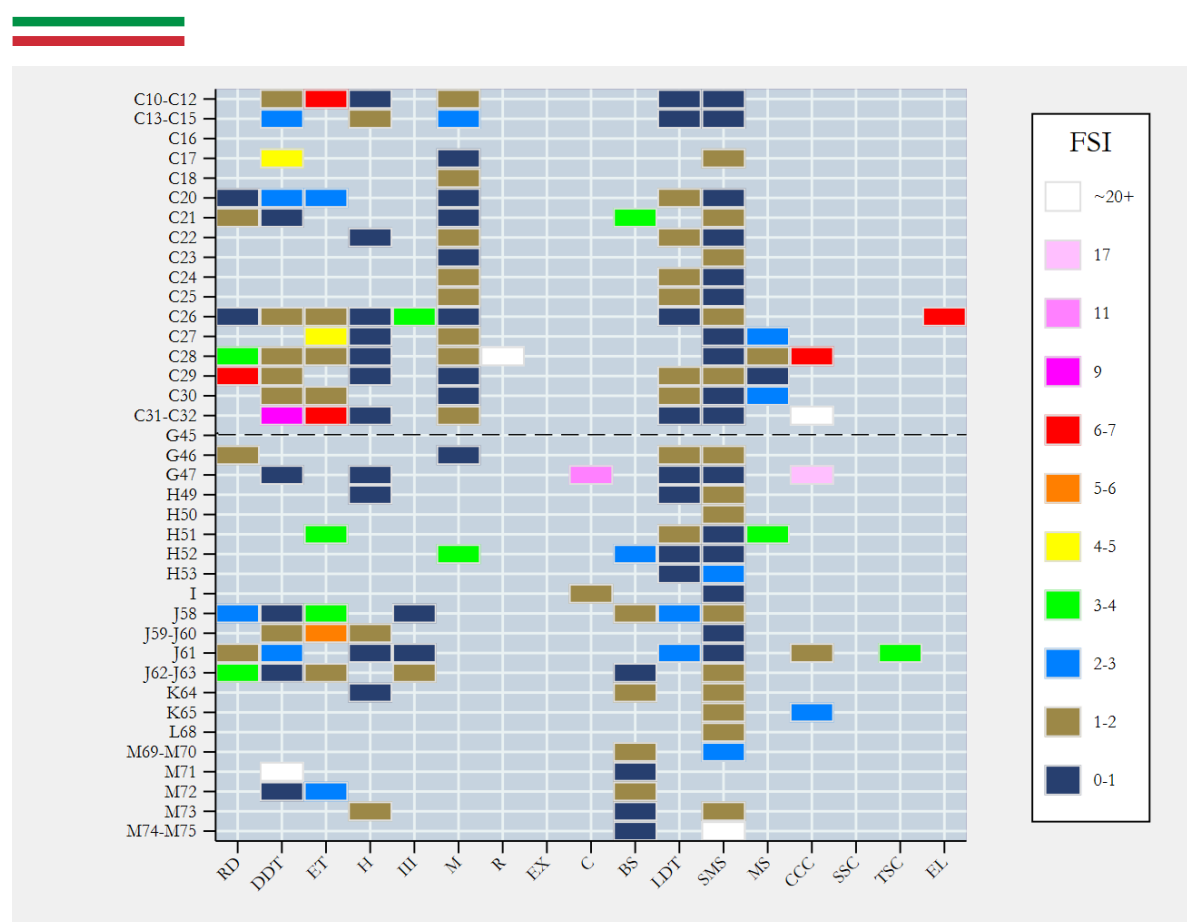


Italy received the fewest FDIs in terms of absolute number over the 2003-2016 period, and they are the least spread out. This is shown by the relative and noticeable absence of colored rectangles in the plot relative to ‘blank intersections’. Second, when Italian industries specialize in a function, they tend to greatly specialize. This is exhibited by the abundance of varied bright colored rectangles relative to light brown ones as compared to the previous plots—i.e. this plot is ‘hotter’.

Third, outside of SMS and, to a much lesser extent, manufacturing, Italy lacks a clear specialization pattern—i.e. there is no one function, narrow category of functions, or broad category of functions that exhibits a cross-industry specialization pattern. This is mostly due to the lack of FDIs (empty intersections) and not the abundance of nonspecialization (**blue rectangles**). If any pattern is to be observed, it is that the manufacturing sector tends to be more specialized in upstream functions, while the services sector specializes in downstream functions, but that is not a strong pattern by any means.

As mentioned, the plot is ‘hot’: industries tend to exhibit high magnitude specializations in the functions they perform, and often only specialize in those functions. This hints at a lack of functional diversification. Outside of the J-sector, service industries tend to be specialized in just one or two functions across all 17.

Figure 6. Functional Specialization & Diversification Heatplot, Italy, 2003-2016 Averages



At the individual level, the FSP strategy adopted above, and the associated presentation procedure (heat plots by industry/function) has some key advantages that should be considered in assessing next steps for this line of inquiry. Similarly, there are certain obvious disadvantages that need to be addressed, as, in the current form, those render the approach misleading and lacking in accuracy if not accompanied by higher level aggregations.

By disaggregating country into industries, the approach adds a horizontal layer (function by individual industry) of granular meaning/detail to the analysis. The country level information remains intact in the vertical layer (function across industries—i.e. by country). For example, a quick glance at the heat plot of the Netherlands above will show that country's lack of specialization in manufacturing (vertical pattern of dark blue across industries in the function, "M")—i.e. the Netherlands is not functionally specialized in manufacturing relative to a sample that includes Spain and France as 41% of the data. Another quick look would also show that J58 is an exception, and that this industry also shows marked functional diversification (at least 1 function in all streams). The ability to simultaneously glean both vertical and horizontal—i.e. function by country and function by industry—trends in the data with ease is the main strength of these plots.

By disaggregating the national economy into 38 industries AND further disaggregating stages of production (pre-, post-, and –production) into 17 function groups, the number of FDIs in a single observation were spread so thin that there are a great many instances of 'too few' FDIs (~1-3). In

dealing with these particular FSIs, one may choose to implement a cut-off, wherein a threshold for the minimum number of FDIs to be considered for the individual FSI scores. Otherwise, the interpretation of FSI is diluted by the frequency of these anomalies, particularly in the cases of Italy and the Netherlands, which respectively account for only 7% and 10% of 16,084 FDI inflows.

To allow for larger statistical significance (more observations backing each data point), and to harness the descriptive and statistical utility of the FSP approach, the different combinations of functional specialization at the industry level must be surmised. In other words, we must aggregate to a higher level (narrow functional groupings). That is, 5 groups as shown in figure 1 above: RD: research and development related functions; HQ: headquarters related functions; PN: production functions; LR: logistics and retail; and SP: support functions. It is at this level where most of the forthcoming analysis of the relationship between the FSPs and innovation will be conducted. As such, a few macro patterns are presented here, with the rest related to the next section.

3.3 | Functional Specialization and Innovation Propensity of EU Industries

To recap, a FSI value greater than 1 denotes the share of FDIs in the given function relative to all FDIs in that industry is larger than the same share observed in the overall population (all industries across all countries). In other words, the function is overrepresented in that industry–region compared to the general distribution, signaling a relative specialization.

For example, Spain’s telecom industry, J61 received 87 FDIs (out of the 347 received in total) by J61 across the 5 countries. As in the other 4 countries, production saw no FDIs (FDI = 0/0 | FSI: 0). R&D activities (FDI = 9/37 | FSI: 0.97) and support functions (FDI = 29/147 | FSI: 0.77) display a relative lack of specialization, while headquarters (FDI = 46/154 | FSI: 1.9) and logistics and retail (FDI = 3/9 | FSI: 1.33) are functions where Spain’s J61 is specialized. France’s “J61” (79/ 347 total FDIs) also specialized in both pre- and post- production, but instead of LR & HQ specializations like Spain, it is specialized in R&D related (FDI: 12/37 | FSI: 1.42) and support functions (FDI: 34/147 | FSI: 1.02).

Italy’s J61 is specialized in LR and RD. The FSI value for Italy’s J61 research and development specialization (FDI: 6/37 | FSI: 1.82) is high because 6 of the 31 FDIs that industry received went towards R&D functions, which is a much higher allocation (20%) than Spain (10%) or France (15%), despite both having received more FDIs to perform R&D than Italy in absolute numbers. Germany’s telecom industry (J61) displays a monocore structure, with specialization confined to the downstream functions of LR and SP. The Netherlands represents the only hyper-specialized J61 case: of 38 total FDIs, 21 were directed to headquarter services, yielding an FSI of 1.25. Although HQ functions are prioritized across other J61 industries, the Netherlands exhibits a comparatively higher concentration in this activity. The trend of HQ specialization, whether exclusively or as part of a more diversified FSP structure, is common for the Netherlands across most industries, as will be discussed in the second part of this chapter.

3.3.1 | Specialization & Innovation at Various Level of GVC Integration

Smile Curve (hierarchy of functions) hypothesis

At its most fundamental level, the smile curve hypothesizes that functions are related hierarchically, with intangible intensive functions commanding greater returns to specialization than their tangible intensive counterparts. Although this hierarchy will be unpacked with greater granularity in the coming section on emergent combinations of intangible knowledge operationalization, for now we will focus on the most established version of this hypothesis, which is that upstream (preproduction) and downstream (postproduction) functions are *better* than midstream (production) functions for value capture and GVC positioning. Since in this paper we are concerned with value in terms of innovation performance, **the hypothesis then becomes:**

$$\underline{H^{A1}} \rightarrow$$

SPECIALIZATIONS IN PRE- & POST- PRODUCTION FUNCTIONS ARE ASSOCIATED WITH HIGHER INNOVATION RATES THAN PRODUCTION FUNCTION SPECIALIZATIONS

$$\underline{H^{A0}} \rightarrow$$

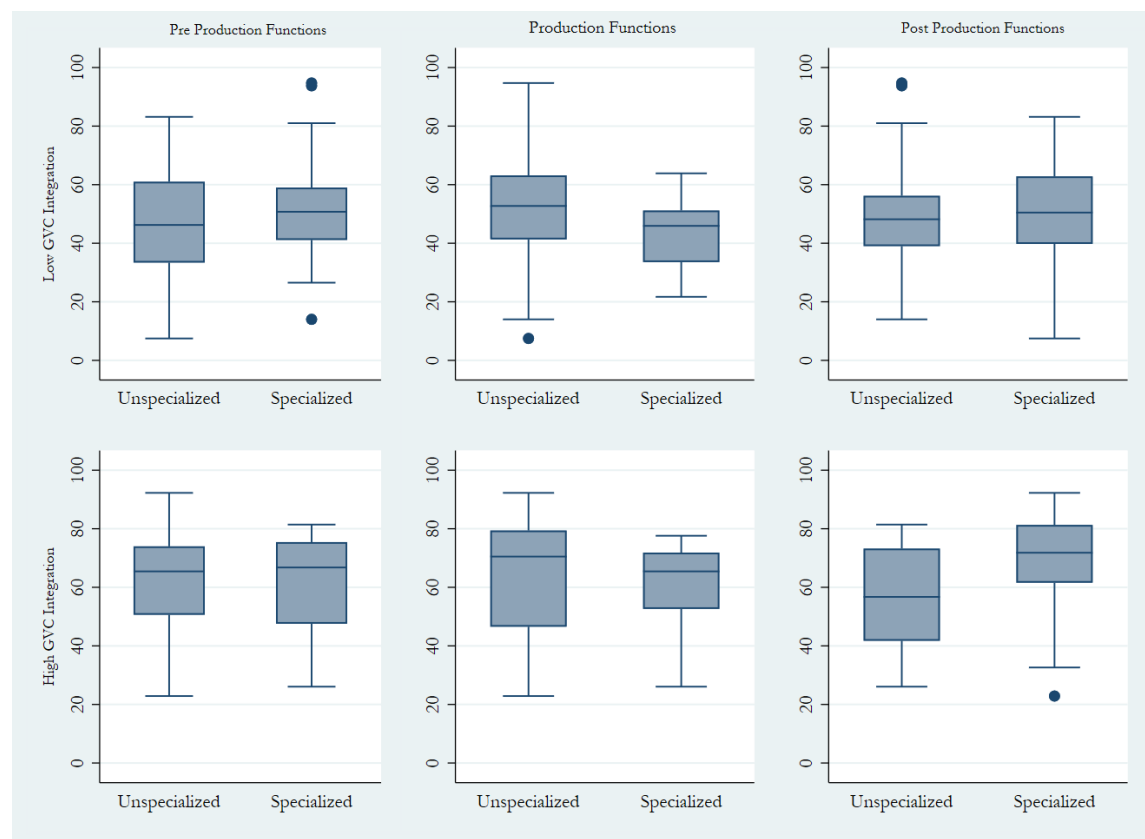
THERE IS NO CORRELATION BETWEEN INNOVATION PERFORMANCE AND SPECIALIZATION ALONG THE SMILE CURVE

Moreover, since the mechanism of action being investigated for linking specialization and innovation is GVC integration, an added layer of investigation concerns viewing the relationship in industries at various levels of GVC integration. As such, the total number of FDIs received by a given industry in each country is set to represent that industry's *relative* GVC integration. The mean number of FDIs received in all industries (after accounting for two significant outliers, Germany's C26 and C28), 72, represents a rough average threshold, below (above) which we can say an industry is relatively unintegrated (relatively integrated). Finally, we expect H1A to be true for all types of innovation, except perhaps (or to a small degree for) process innovations, which are notoriously linked to production activities that require a great deal of process flow & coordination for manufacturing and assembly lines (see relevant discussions in chapters 2 and 4).

We examine general, product, process, and organization innovation propensities of 186 European Industries from the 5 largest economies—Germany (DE), Spain (ES), France (FR), Italy (IT), and Holland (NL)—cross sectionally between 2003 and 2016 given a binary condition of specialization (0/1 | no/yes) in preproduction, production, and postproduction linking functions at two levels of GVC integration.

Apart from process innovation, which either slightly increases or decreases when toggling the condition of specialization in production functions, all other forms of innovation (general, product, and organizational) are significantly lower for industries specialized in production functions, and higher for up- and down- stream functional specializations, with a lean towards the latter. The trend for the share of firms introducing general innovations—**figure 7 (below)**—is representative of the disaggregated types of innovation as well (product and organizational, more so than process).

Figure 7. Share (%) of Firms Introducing General Innovations by FS & GVC Integration



Each column in Figure 7 represents a specific stage of production, while each row represents two GVC integration levels based on the number of inward FDIs received, given a mean of 72 FDIs as the threshold. **This gives 12 box plots. The number of observations is large for each of the specialized plots, ranging from a minimum of 23 industries (production, high GVC integration) to a maximum of 56 (preproduction, low GVC integration).** This makes for highly significant results as each industry specialization contains dozens to hundreds of data points (FDI projects) across 16 years.

Each graph contains two boxes, comparing industries that are "Unspecialized" (0) vs. "Specialized" (1) in that specific function, using mean innovation propensity of an industry (*q_{inno}*) as the innovation variable. In both integration contexts (top and bottom rows), industries specialized in pre-production and post-production (right-side boxes in columns 1 and 3) generally show **equal or slightly higher median innovation scores** than their unspecialized counterparts. This aligns with the smile curve hypothesis: intangible-intensive (upstream/upstream) specialization “commands greater returns to specialization.”

This is particularly obvious in the case of postproduction specialized industries given a high level of GVC integration, where the mean, median, minimum, and maximum observations for the specialized industries all outperform the unspecialized industries in terms of share of firms introducing general innovations. The average share of firms introducing general innovations in industries unspecialized in downstream functions (39 industries) is 57%, which increases to just below 70% given the same level of GVC integration, we consider industries that are specialized in downstream functions (36 industries). For product innovation (not shown in figure 8), the share of firms introducing innovations at a high level of GVC integration are 34% (unspecialized) and 43% (specialized). Organizational innovation shows a similar trend, while process innovation shows no difference whatsoever between the unspecialized and specialized groups at high (both ~ 32%) and low levels of GVC integration (both ~ 27%).

The association between upstream functional specialization and innovation performance is generally similar with some key differences. First, specialization in preproduction functions seem to be associated with higher innovation performance more so at lower levels of GVC integration. In terms of industries ‘unspecialized’ in preproduction, 47% of firms introduced general innovations, while 53% of firms did so in preproduction specialized industries. While at high levels of GVC integration, both figures hover around 60%. This trend holds for all 3 disaggregated types of innovation across both levels of GVC integration.

The association between midstream functional specialization and innovation performance is the opposite. 52% of firms unspecialized in production introduced general innovations while that figure falls to 43% for the industries specialized in the production functions such as manufacturing, recycling, construction, and extraction. In terms of the innovation types, most affected seems to be product innovation with the share of firms introducing product innovations falling from 29% to 20% when specialization is toggled (one of the lowest figures across the whole dataset) and 33% (unspecialized) → 28% (specialized) for organizational innovation. The only unaffected innovation type seems to be process innovation (28%-26%), which is consistent with expectations (see page 21).

More so for production specializations, while this is exactly in line with the hypothesized results, that is only the case for low levels of GVC integration. At high levels (FDI>72), the following average innovation rates are observed by innovation type (unspecialized | specialized): general (63% | 61%), product (38% | 39%); process (31% | 36%); and organizational (39% | 39%). **The share of firms introducing process innovations seems to benefit from specialization in production.** However,

this is strongly mitigated by the fact that at higher levels of GVC integration, few major European economies seem to demonstrate hyper specialization in production functions. As such, we must also control for that aspect of the functional specialization profiles (FSPs) at this stage—namely, we must control for ‘number’ of relative specializations, which affects the returns accruing to diversification and the emergent benefits due to complementary functional specializations (combinations). In other words, we must compare within not between functional specialization profiles.

We will consider the innovation performances associated with **hyper specialized industries** (only 1 functional specialization) at the second level of aggregation (out of 5). 79 industries present hyper specialized FSP structures. The average innovation rates of these industries are as follows: general innovation: 53%, product innovation: 29%, process innovation: 28%, and organizational innovation: 35%. We will compare different functions given these baselines at different levels of GVC integration. The average number of FDIs received by all hyper specialized industries is 70.¹⁷ As such, that number will be used as a rough threshold below (above) which we can say that an industry is relatively unintegrated (relatively integrated) in hierarchically governed global value chains. An important caveat to note at this point is that there are only 2 industries in the entire dataset that are hyper specialized in R&D functions, which, while lending interesting descriptive evidence for the *brain and brawn* hypothesis, makes it impossible to include it in the analysis. As such and given the discussion above concerning the common coupling of R&D and production functions, industries presenting this combination of specialization will be considered in this part of the analysis (only) as hyper specialized in research and development related functions. This discussion will be unpacked with greater attention later.

Table 1. Innovation Propensity in Hyper Specialized Industries

GVC Integration	Function	RDR	HQ	P	LR	SP
% firms introducing General innovations (# obs): if less than 5 industry-observations ¹⁸						
Low	Unspecialized	48%	48%	50%	48%	46%
	Specialized	52%	47%	41%	51%	51%
High	Unspecialized	65%	67%	65%	65%	57%
	Specialized	65%	50% (3)	59% (3)	58% (4)	74%
% firms introducing Product innovations						
Low	Unspecialized	24%	23%	26%	24%	22%
	Specialized	31%	26%	17%	25%	26%
High	Unspecialized	41%	42%	41%	43%	33%
	Specialized	45%	31% (3)	37% (3)	27% (4)	50%

¹⁷ Germany’s C26 (FDI: 647) and C28 (FDI: 757) industries were removed from this simple step of calculating average inwards FDIs simply since they both received many times more than the average and about double the third most industry. The average FDIs received drops from 92 to 70 when they are excluded. That said, this is simply a reference, meant to guide the selection of levels of ‘GVC integration’ and their exclusion or removal does not alter the results. In fact, the average innovation rates remain the same regardless.

¹⁸ This matters in the case of a trend break instead of trend continuity, which occurs in the case of HQ and LR functions. As such, those results should be considered as mere suggestions for further analysis, and not as evidence. The low observations results related to Production are trend continuous and so can be more instructive (the low number is representative of the general trend).

% firms introducing Process innovations						
Low	Unspecialized	26%	27%	27%	27%	25%
	Specialized	29%	25%	25%	26%	28%
High	Unspecialized	31%	31%	30%	32%	29%
	Specialized	35%	29% (3)	37% (3)	24% (4)	33%
% firms introducing Organizational innovations						
Low	Unspecialized	33%	34%	35%	33%	34%
	Specialized	29%	37%	30%	37%	34%
High	Unspecialized	40%	42%	41%	39%	38%
	Specialized	43%	32% (3)	38% (3)	42% (4)	43%

An immediate pattern discerned from table 1 (above) concerns production (P). Across all innovation types, given both low and high GVC integration, **hyper specialization in production is associated with a lower percentage of firms introducing innovations.** Given how this analysis is set up (within FSP not between FSPs), we are comparing 1 hyper specialization against the average of all other hyper specializations). For example, an average of 17% of low-integrated firms in industries specializing in production introduce new product innovations. That figure is relatively far below the 26% of firms introducing product innovations in industries hyper specialized in either RDR, HQ, LR, or SP. The same trend holds for general innovations with the average number of innovative firms in intangible specializations being 50%, while only 41% of firms specialized in production are innovative.

At high levels of GVC integration, however, the same trend is observed, however, at a much lower substantive and statistical significance. This points to a relationship between the sheer number of FDIs and innovation rates, outside and irrespective of the type of specialization. This point becomes highly relevant as the present chapter continues and is tackled particularly in the next subsection alongside the discussion of functional diversification. For now, however, it suffices to note that even while controlling for GVC integration (number of FDIs) and the number of specializations in the functional profile (comparing hyper specialized industries only), **midstream specialization is associated with lower innovation performances across the board, with, again, the single exception of process innovation, in exact line with our hypothesized results.**

We also observe that the share of innovative firms in industries hyper specialized in headquarters (HQ) and logistics & retail (LR) functions does not differ from the average outside of these functions. In other words, hyper specializing in HQ and LR functions does not seem to affect innovation rates in any meaningful way beyond the fact of hyper specialization (i.e. when compared to average indicators across the other functional groups). RDR functions seem to matter most for product innovations where RDR hyper specialized industries outperform the HS average (outside of RDR) by a somewhat significant margin as can be seen from the above table. However, a general increase in innovative firms is seen across the board for RDR specialized industries within the hyper specialized (HS) group.

In terms of support functions, the strongest relationship is observed. Across all comparators, hyper specialization in SP is associated with much higher innovation rates than hyper specialization in any other function. This trend is most pronounced in GVC integrated industries. While the average number of innovative firms in the low GVC integration category goes up from 46% to 51% given

hyper specialization in SP, that same figure goes up from 57% to 74% given a high level of GVC integration. Similarly, the percentage of firms introducing product innovations is substantively higher for industries hyper specialized in SP: from 33% to 50%. Both of these figures (74% & 50%) are much higher than their counterpart averages, and are some of the highest in the dataset.

At all levels of aggregation, production specialization and production hyper specialization (HS) in 1-specialization industries is associated with the lowest innovation performances out of any other specialization. As a final series of evidence on the matter, consider the FSI indicators at the highest level of aggregation in table 2 below, which shows, yet again, that production specialized industries suffer from the lowest innovation performance across all specialization broad groups, and the case is worse for hyper specialized industries. The same is true also for upstream HS, but not downstream HS. As suggested prior, this has to do with the effect of a single country disproportionately specialized in downstream functions, Germany. This discussion will be taken up towards the end of the chapter.

Table 2. Share of Innovative Firms Per Industry by Smile Curve Functional Groups

SC Function	#obs (HS)	General (HS)	Product (HS)	Process (HS)	Organizational (HS)
Upstream	86 (12)	55 (50)	32 (29)	31 (26)	34 (36)
Production	57 (11)	50 (46)	28 (22)	30 (28)	32 (32)
Downstream	85 (35)	57 (58)	33 (32)	29 (29)	36 (38)

As table 2 (above) shows, the worst innovation performance when considering the highest level of aggregation), is related to production only specializations. 11 industries across our 5-country sample specialized only in production functions between 2003 and 2016 on average. These 10 industries are a mix of Spanish, French, and Italian industries, mostly manufacturing Scale and Information Intensive (SII) industries.

These industries are outperformed by averages across all innovation metrics in data. Upstream only specializations fare slightly worse than preproduction specialized industries that boast other specializations as well in all but the organizational innovation indicator. Hyper Specialization in downstream, however, does not seem to affect returns to specialization in terms of innovation performances whatsoever. These results are consistent across innovation groups, levels of aggregation of functional specialization, and across low and high numbers of inwards FDIs, which is here used as an indicator for GVC integration.

Given these findings, we can reject the null hypothesis, HA0, in favor of the alternate, HA1, finding that specialization in pre- and post- production is indeed associated with higher innovation rates across the board (however with varying degrees) than specialization in production. This finding is consistent across and between FSP groups and is strongly pronounced for production-hyper-specialized industries, which have been found to demonstrate the lowest innovation rates across all indicators and FSP groups. **Therefore, we provide new evidence at the industry level for the hypothesis that value capture in terms of innovation capacity is associated with specialization along the smile curve.**

However, there does not seem to be an increased intensity of the relationship at higher levels of GVC integration. Moreover, thus far, the number of FDIs has been used as an indicator for GVC integration, however, as has been suggested in the analysis here, there is an association between the number of inwards FDIs and innovation outside of specialization patterns. The next section will flush out this relationship, controlling for it, and showing that even when this relationship is neutralized, the primary subject of interest, the specialization/diversification-innovation nexus, remains strongly significant.

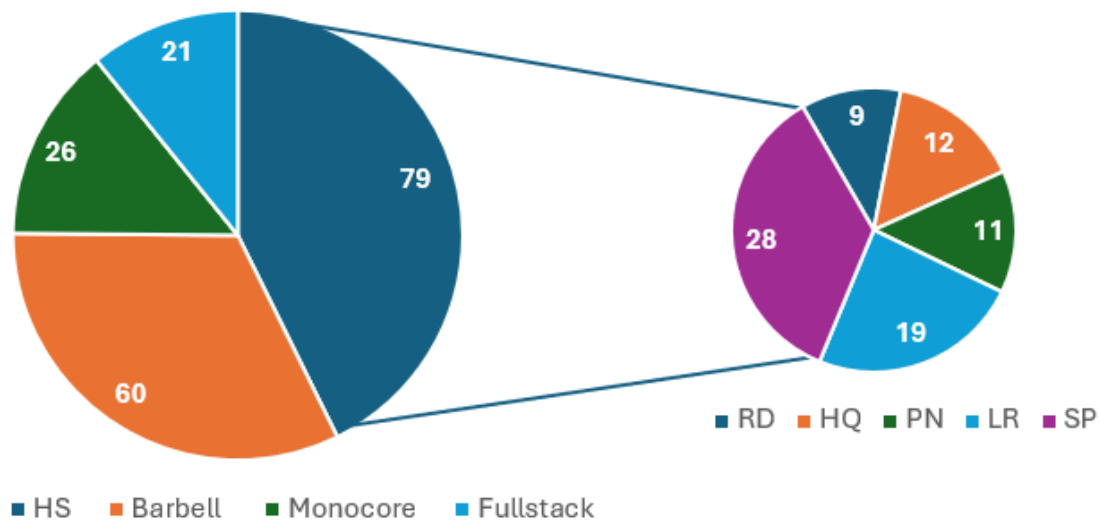
3.3.2| Functional Combinations & ‘Smile Tilt’

The preceding analysis provides a granular empirical map of how functional specialization in GVC-related trade is linked to innovation propensities of European industries. The implications of these patterns are salient. The most immediate is the confirmation that GVC participation does not affect a homogenous benefit. While the data shows that high GVC integration (measured by FDI volume) is generally associated with higher innovation rates, the functional quality of that integration acts as a ceiling or a floor. **Industries specialized in production (the "brawn" of the value chain) face a systematic innovation deficit compared to those specialized in intangible-intensive functions (the "brains").**

In our analysis, we could not test claims emerging from the 'brain and brawn' hypothesis (see Chapter 1: 1.2) that a combination of both is optimum (Buciuni & Pisano, 2021). This is because Germany is the only country maintaining its manufacturing core, and only in a few industries. With a different geographic scope, however, the idea that a combination of tangible and intangible functions in the specialization profile of an industry is superior innovation propensities could be investigated.

In fact, the data points to the emergence of various other combinations than 'brain and brawn'. Of the 190 European industries in the dataset, 4 have received absolutely no FDIs between 2003 and 2016; of the remaining 186, the following specialization types are discovered. 79 industries are hyper specialized in single function groups only: RD: 9; HQ: 12; PN: 11; LR: 19; SP: 28. 60 industries are *Barbell* shaped, meaning they are specialized in exactly 1 group of upstream functions (RDR or HQ) and one group of downstream functions (LR or SP). There are 26 Monocore industries, conceptual opposite of barbell industries in terms of diversification of functional positioning: these are industries specialized in both narrow groups of upstream or downstream functions (13 of each industry exists in the data). Finally, 21 of what is being termed *fullstack* industries exist: industries specialized in at least 1 function in all streams.

Figure 8. European Industries by Specialization Type (FSP), 2003-2016 total



The data suggests a curious pattern where even though Barbell industries are the most common type of industry profile (60) in European industries, their Monocore counterparts (26) outperform them in terms of innovation rates across all innovation types. For example, the average number of innovative firms in monocore industries is 60%, while the same indicator for barbell industries is 53%. This pattern holds across disaggregated innovation types. **While this simple statistic is not sufficient to make any confirmatory claims, it does indicate how other functional combinations and theories may be explored. For example, it may be that the difference between monocore and barbell industries could shed light on the dynamics of GVC deepening, an underexplored topic according to Morrison et al. (2008), who argue it is overshadowed by the notion of upgrading.**

More interesting, while the two industry types are spread equally across countries with each of the 5 countries each having almost exactly 5 monocore industries and around 12 barbell industries (7 in the case of Italy and 15 in the case of the Netherlands), monocore industries are only better for innovation in Germany, Spain, and France; while in the case of Holland there is no discernible difference and in Italy barbell industries significantly outperform their monocore counterparts. This suggests unit heterogeneity in how the two industry FSP types affect innovation.

Furthermore, postproduction barbell industries tend to be far more innovative than preproduction barbell industries. In fact, **a striking finding in this study is the outsized association of downstream specializations with innovation propensity at the industry level, especially as concerns Support Functions (SP) specializations.** Traditionally, economic intuition and a large body of empirical work would lead us to expect R&D—and, to a lesser extent, branding—to occupy the highest positions in value capture and innovation performance. Yet the evidence here points in a different direction: in highly GVC-integrated contexts, specialization in support functions is associated with the highest innovation rates, reaching 74%, and even exceeding R&D.

This suggests that in modern, complex GVCs, the "glue" that holds the chain together—logistics coordination, organizational management, and specialized business services—has become a primary engine of innovation. This "Support Function Paradox" indicates that innovation in 21st century Europe is increasingly organizational and systemic rather than purely technical. For firms, the competitive advantage may no longer reside in what they invent (R&D), but in how they coordinate the global operationalization of those inventions (Support Functions).

There is, however, another interpretation for this result, and in line with GVC studies: different countries seem to benefit differently from the various intangible assets linked to their functional counterparts. This is not only to say that the *coefficient* (size/magnitude) of the substantive effect of specialization and diversification on an industry is different, but also that is based on the functional profile of the wider structure (nation).

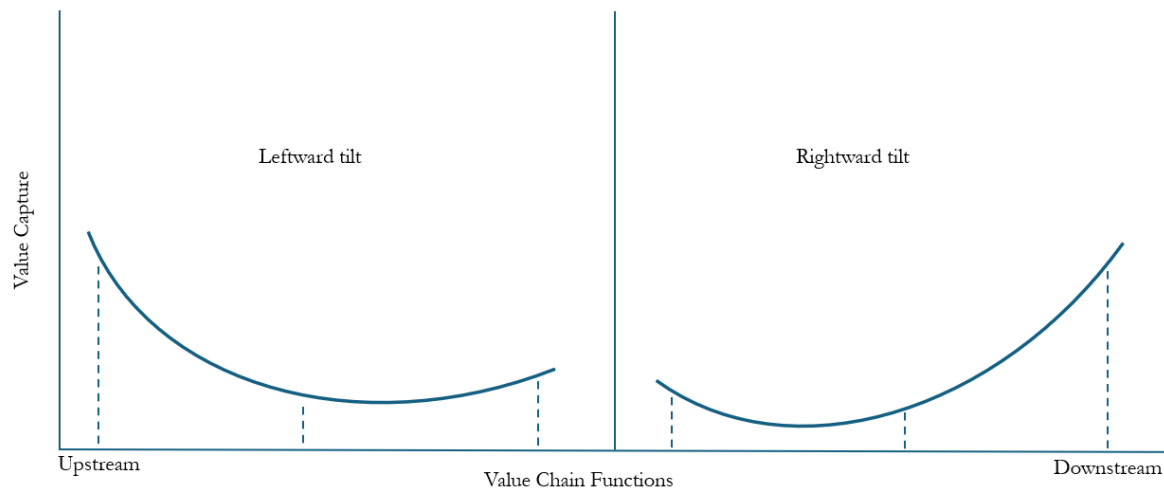
Consider that Germany and Italy are more specialized in post-production, both with 18 industries specialized in downstream functions relative to their 14 and 11—respectively—upstream industry specializations; while Spain (21 *pre* & 11 *post*) and France (18 *pre* and 11 *post*) present the opposite specialization trend. The Netherlands is the most equitable on both sides in terms of inwards FDIs (24 *pre* and 18 *post*), leaning more towards the profiles of Spain and France (upstream tilted) than those of Germany and Italy.

Table 3. Broad Functional Specialization Count by Country and Share of Generally innovative Firms

Country	PRE	POST
DE <i>qinno</i>	14 71%	18 75%
ES <i>qinno</i>	21 46%	11 35%
FR <i>qinno</i>	18 55%	11 46%
IT <i>qinno</i>	11 49%	18 51%
NL <i>qinno</i>	24 55%	18 55%

Patterns of innovation return to specialization seem to correlate to functional specialization at the national level. Germany contains slightly more industries that are downstream specialized, and the general innovation rate of these industries is 4% (additively) higher than their upstream counterparts; the trend is reversed in Spain, where the 21 industries specialized in preproduction contain an average of 46% innovative firms, while in the 11 downstream specialized industries, 35% of firms are generally innovative. As shown in table 3 (above), France demonstrates the same pattern, while Italy and the Netherlands show a negligible difference.

Figure 9. Smile Tilt



As such, it does seem that (1) different intangible combinations of functional specialization profiles matters for innovation performance, and that (2) partly the determinant of this may be associated with relatedness to the wider, national functional *tilt*. For example, the most leftward tilted German industries average 68% innovation propensity, while the most rightward tilted ones show an average of 76% innovative firms (*qinno*), **perfectly in line with the national specialization**. All other innovation types are consistent with this trend, and the trend is reversed for Spain and France, where, respectively, their left-tilted industries show 46% and 58% innovative firms, as opposed to 35% and 49% in the rightward tilted industries that go against the national average specialization *tilt*. Italy and the Netherlands follow suite; for example, Dutch product innovation in leftward tilted industries is significantly high at 41%, higher than the national average of 33%, the average across the entire sample (30%), and, most importantly, the average across rightward tilted Dutch industries, 29%.

Indeed, the idea of functional relatedness is established in Evolutionary Economic Geography studies. EEG studies found that the capacity of regions to upgrade functionally is path-dependent, contingent on the existing portfolio of related functions and the complexity of those functions. Empirical evidence from recent studies demonstrates that regions are more likely to develop new specializations in functions that are already present or related to their existing capabilities (Hernandez-Rodriguez et al., 2025).

What is being suggested here is that this argument also works for functional deepening: At high levels of integration, the number of FDIs begins to matter less than the vocation of those FDIs. The data indicates that once an industry is sufficiently integrated, the marginal return on "more" integration is lower than the return on "better" specialization. This topic is picked in up Chapter 4 in greater detail.

This shifts the focus of industrial strategy from quantitative metrics (number of projects, total capital investment) to qualitative alignment. The case studies of Spain, France, and the Netherlands illustrate that these are not merely descriptive variations but distinct national vocations. Whether a nation positions itself as the “lab,” the “hub” (the Netherlands’ HQ specialization), or the “logistics node”

(Germany's downstream focus), it is making a high stakes bet on its future innovation capacity. The evidence suggests that being the "hub" is superior to being the lab in terms of a robust path to innovation-led growth, and both are far more favorable than the "factory" model, which increasingly presents with an innovation ceiling.

Given these *suggestions* by the data, and the theoretical foundation provided by EEG scholarship, this section concludes with suggesting a hypothesis to be tested by future studies

The *Smile Tilt* hypothesis (from volume to vocation)

$H^{B1} \rightarrow$

INDUSTRY RETURNS TO SPECIALIZATION ARE GREATER IF IN LINE WITH THE NATIONAL FSP

$H^{B0} \rightarrow$

RETURNS TO SPECIALIZATION AT THE INDUSTRY LEVEL ARE NOT CONDITIONED BY THE COUNTRY-WIDE SPECIALIZATION

This is an exploratory hypothesis suggested as part of the interpretation of the results found above. **Aside from that, the analysis consistently shows that specialization in production is associated with the lowest innovation performances across almost all types of innovation, with the sole exception of process innovation. This is a confirmation of the hypothesis set out to be tested by this paper.**

The implication is clear: in high-cost European economies, production specialization, at least those without a corresponding link to R&D, HQ (for Holland) or Support Functions, is an innovation dead-end. The data suggests that process innovation—the only type that benefits from production specialization—is insufficient to offset the decline in product and organizational innovation. This creates a “specialization trap” where industries become highly efficient at processes that are increasingly commoditized, leaving them vulnerable to lower-cost competitors elsewhere in the GVC.

This is in line with previous theories and empirical evidence. Recall from Chapter 1 the conceptualization of innovation as a capacity under constraints that can and often do lead to ‘lock-ins’. In the case of production specialization, particularly hyper specializations, the stagnation seen innovation propensity is likely due to lock-in in that sense. As argued by Coveri and Zanfei (2023), hyper specialization imposes a great limit on sustainable innovation capacity. The results presented are in line with this suggestion but argue that various combinations of specializations constructing what has been termed ‘profiles’ also carry different relationships with innovation, opening the door for future research by FSP.

3.4| Functional Diversification & Innovation Propensity of European Industries

Functional diversification is defined in terms of the relative breadth or concentration of specializations across a coherent economic geography (for example, an industry or a nation). Given the increasing rate of technical change and the deployment of new innovations and methods for operationalizing intangible knowledge, it comes as no surprise that a strand of the GVC literature exploring the functional lens is concerned with the relationship between functional diversification and value capture. Recall from earlier that going as far back as 7 decades this idea has been present in literature.

Specifically, Penrose (1959), suggested that the wide array of activities that constitute innovation require a ‘wide breadth’ of intangible assets working in unison. More recently, Montessoro & Vezzani (2016) argue that “the multiplicity of intangibles enables the investing firm to embark in the different activities that constitute the innovation process at the firm level” (Montessoro & Vezzani, 2016: 333). In frameworks such as TC that consider intangibles as assets, their ‘multiplicity’ seems to provide emergent qualities to firms deploying them—meaning returns bigger than any individual specialization commands. This is sometimes referred to as the ‘complexity approach’.

In their paper, *The Virtues and Limits of Specialization*, Coveri & Zanfei (2023) explain how this approach departs from standard economic theory:

This line of research leads to a result quite opposite to the one reached in standard economic literature, according to which countries should specialize in the few industries in which they have a comparative advantage [...] the key conceptual message to be drawn from this “complexity approach” is rather that economic development of countries is driven by their level of productive diversification, especially into products that are incrementally more complex. [...] The emergence and evolution of GVCs induces a re-consideration of the specialization *versus* diversification argument. In fact, it appears that the issue at stake is not the degree of specialization – or diversification – of economies at the product level. It is rather a matter of specializing – or diversifying – into *functions* within individual industries (Coveri & Zanfei, 2023: 77-78)

In addition to this ‘virtue’ deriving from board intangible knowledge assets, there is a ‘limit’ to hyper specialization in terms of “a narrower production matrix, reduced learning opportunities and a lower amount of tacit knowledge circulating across domestic actors” (ibid, 82), thus leading to lower overall lower innovation performances.

The same authors, in other studies, also link diversification with improved environmental performance and increased resilience to and faster recovery from economic shocks (Coveri et al., 2024). Unfortunately, the findings concerning diversification and climate change fall outside the empirical scope of this PhD thesis, however, in the following chapter the relationship between diversification and economic resilience is explored using the same data, but with the time dimension reintroduced. **For this chapter, however, the sole concern remains whether diversification is associated with innovation propensity of industries in any meaningful way, especially given that the link between diversification and innovation is arguably more theoretically flushed out than that between the latter and individual or grouped functional specialization *per se*. Following this argument, we put forth our research hypothesis:**

$H^{C1} \rightarrow$

MORE DIVERSIFIED INDUSTRIES ARE ASSOCIATED WITH HIGHER INNOVATION PROPENSITIES

$H^{C0} \rightarrow$

THERE IS NO CORRELATION BETWEEN INNOVATION AND FUNCTIONAL DIVERSIFICATION

3.4.1 | CV_FSI & HHI

To accomplish this, we compute a simple Coefficient of Variance of the FSI index (CV_FSI), which will be the main indicator throughout the rest of this chapter. As the name indicates, CV_FSI measures the variance between all FSI scores in a single industry/country. As a form of robustness check, diversification was also measured using other formulas including the Herfindahl–Hirschman Index (HHI). These 2 variables capture the same information, and both are used for every calculation below as a robustness check for the results. No divergence in results is found. In fact, the correlation between the 2 indicators is nearly perfect at 0.96 with 186 observations and statistical significance at the 99.999% level. Going forward, the CV_FSI variable is the one reported, and, unless otherwise specified, it should be assumed that the HHI gives nearly identical results. The exact values can be recomputed using the data and annotated steps annexed to this chapter.

The coefficient of variation is a commonly used statistical measure when its various benefits conceptually align with the objectives of the analysis. Given the nature of the FSI calculation (and the different categorical meanings of different FSI scores), and the fact that we want to capture both specialization by scale (magnitude of 1 FSI score) and scope (type of spread of all FSI scores in an industry), the coefficient of variation has a highly attractive quality concerning its conceptual interpretation when applied to FSI:

CV_FSI is influenced by both scale and scope of specialization—i.e. magnitudes and spread—but is not changed when values are scaled up or down proportionally, meaning hyper specialization by scale is negligible when matched across functions within the same industry, yet highly impactful when unmatched by other large FSI scores. This perfectly defines the diversification that is driving the theoretical basis for this calculation, thus allowing for within- and between- country comparisons of functional diversification by industry.

186 CV_FSI scores in total are computed, for each industry (38) and country (5) pair (190) minus 4 missing observations in the following manner:

Step 1: Mean Functional Specialization of Industries

$$\mu_{FSI} = \frac{\sum_{f=1}^n FSI_f}{n}$$

Step 2: Standard Deviation of Functional Specialization of Industries

$$\sigma_{FSI} = \sqrt{\frac{\sum_{f=1}^n (FSI_f - \mu_{FSI})^2}{n}}$$

Step 3: Coefficient of Variance

$$CV_{FSI} = \frac{\sigma_{FSI}}{\mu_{FSI}}$$

Table 4. The CV_FSI Variable

Variable	Min	Max	Mean	SD	Skewness	Kurtosis
CV_FSI	0.766	4.123	2.124	0.779	0.664	3.133

In terms of the lowest level of aggregation (individual functions), the minimum value of ~ 0.77 belongs to Germany's manufacturing of computer, electronic, and optical Products (C26), a science based, high tech, manufacturing industry that received the second highest number of FDIs in Germany with 757. DE's C26 also holds the third position in Germany (4th globally) out of 38 German (190 globally) industries in average percentage of firms introducing innovations with almost 90% of firms doing so across all 4 CIS waves. It holds the number 1 position globally for share of firms introducing product innovations at 72%, the 6th position in Germany (14th globally) for share of firms introducing process innovations at 44%, and the 10th position in Germany (14th globally) for share of firms introducing organizational innovations.

The maximum value of 4.12 is a common and controversial figure that will be repeated many times throughout the next few pages. The exact value of 4.123106 is given to 7 industries in the sample of 186 (190 minus 4 that received no FDIs). These 7 industries—NL-H50, IT-H50, NL-K65, IT-L68, IT-C18, NL-H53, and FR-G45—are entirely excluded, in the manner outlined below, from the analysis, as their CV_FSI scores are relatively meaningless having all received less than 10 FDIs in the years between 2003 and 2016 (with the exception of NL-K65, which received 11). However, this raises an important question, especially given that the data also reports that these 7 industries are also industries that are particularly lagging in their innovation performance: *is it the lack of FDIs or the lack of diversification of functions performed using those FDIs that is linked to the poor innovation performance, if either?*

Table 5. CV_FSI and Innovation Variables Correlations

Innovation Variable	Correlation with CV_FSI	Number of observations	Statistical significance $P > t $
General Innovation <i>qinno</i>	-0.467	182	0.000: Statistically significant at the highest possible level
Product Innovation <i>qinpdt</i>	-0.513	182	0.000: Statistically significant at the highest possible level
Process Innovation <i>qinpcs</i>	-0.368	182	0.000: Statistically significant at the highest possible level
Organizational Innovation <i>qinorg</i>	-0.319	180	0.000: Statistically significant at the highest possible level

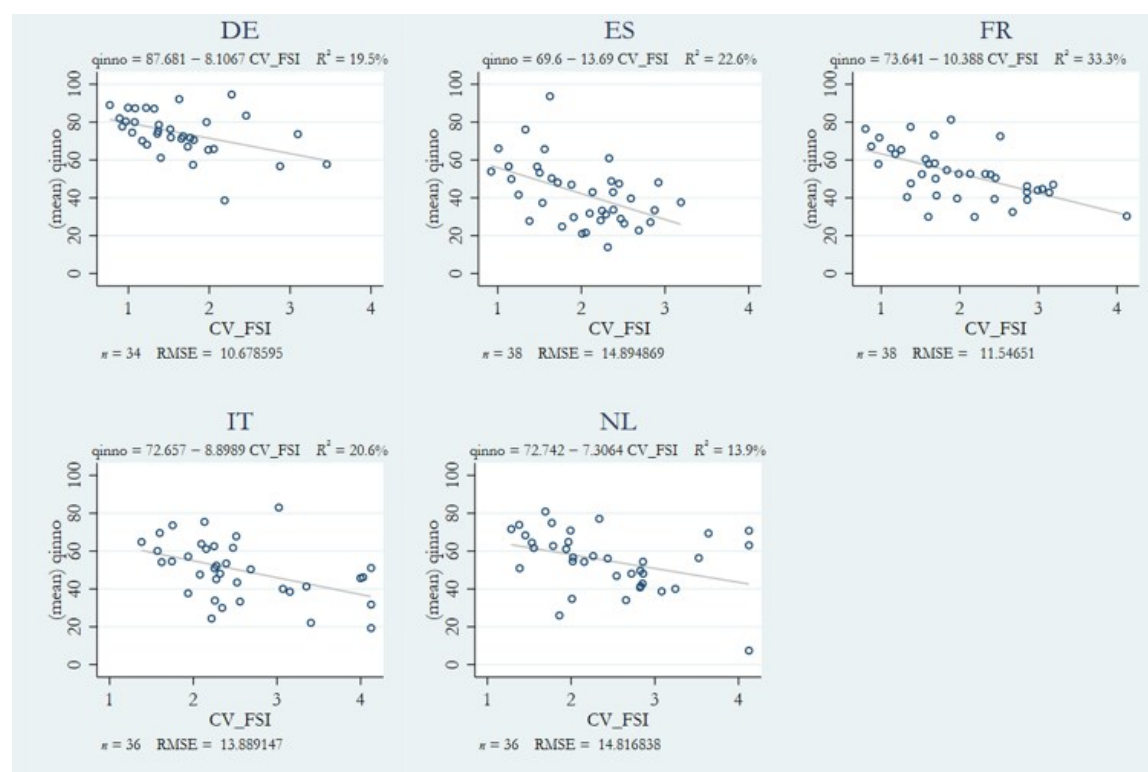
3.4.2 | Diversification and Innovation at the Industry Level

We begin the analysis with a simple correlation table 5 above, on the layer 1 aggregation of the data. The correlation takes negative values in the table because lower values of the indicator used (CV_FSI) mean higher diversification (and *viceversa*). With variations across 180+ observations of industry/country pairs, diversification displays significant substantive and statistical correlated with various types of sectoral innovation. The strongest correlation is between product innovation and diversification with more than 50%; process innovation exhibits a lower benefit from diversification with a correlation of 37%; and 14% between CV_FSI & process innovation only. Organizational innovation is nearer to process's than products' impact of diversification. However, all correlations are statistically significant: enough variation was observed to

determine that the observed correlations between CV_FSI and all but the process innovation only (significant at the lowest, 91%, level) innovation variables are significant at the at the 99% level.

The *aplots* below show the plot of CV_FSI versus share of firms introducing innovation (qinno), product innovation (qinprd), process innovation (qinpcs), and organizational innovation (qinorg). Here, we are mainly interested in (1) the position of the line of fit, (2) the slope of the line, and (3) the R^2 value, which tell, respectively, the relative innovativeness of the countries, the unit effect of diversification on innovation, and the amount of variance in the innovation variable that is explained by the coefficient of variance of FSI, i.e. the diversification score. The RMSE can be considered for a measure of the average deviation of the predicted (line) from the observed (dot) value.¹⁹

Figure 10. Share of Firms Introducing General Innovations by Functional Diversification



¹⁹ NOTE that the statistical analysis performed by Stata's user-created command, *aaplot*, is the same as *reg*. As such, the above graphics can be interpreted in much the same manner as a single variable regression. A P-value that allows for rejecting the null hypothesis at the highest absolute confidence level should be assumed in all 4 relationships.

Figure 11. Share of Firms Introducing Product Innovations by Functional Diversification

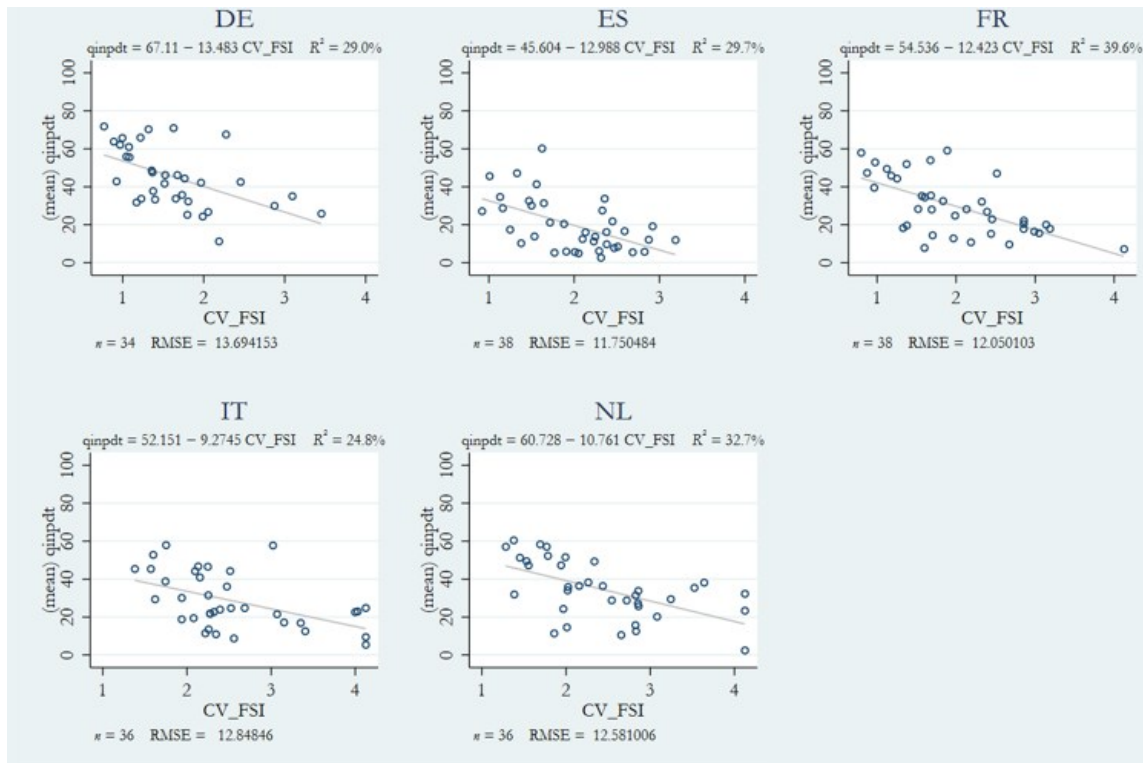


Figure 10 (above) shows France with the strongest positive relationship ($R^2 = 33.3\%$) between diversification and general innovation, given a slope of -10.388 indicating that increased functional diversity substantially boosts innovation. Germany's high baseline (87.681) combined with its -8.106 slope suggests it benefits significantly from diversity while maintaining high innovation levels. Spain consistently shows the steepest slopes across this, and all other, innovation types.

The strongest positive relationship between product innovation and individual function FS diversification appears (figure 11, above) in France ($R^2 = 39.6\%$) and the Netherlands ($R^2 = 32.7\%$). Germany's steep slope (-13.483) represents the strongest positive effect of functional diversity on product innovation among all countries. The varying intercepts (Germany: 67.11%, Spain: 45.604% of firms introducing product innovations) suggest different baseline innovation capacities, but all countries show substantial benefits from increased functional diversity.

It is important to note that even in the countries that do not contain any of the 7 industries with a CV_FSI score of 4.12 (see discussion in previous pages of this section), the relationship remains strong, even stronger than in the countries that do. As will be seen later, this does indeed mean that the relationship between diversification and innovation is significant even outside the relationship between number of FDI's and innovation.

In terms of process innovation (figure 12, below), while showing weaker relationships overall, the negative coefficients still indicate positive effects of functional diversity. France leads with $R^2 = 30\%$, showing the most consistent relationship. **The more moderate slopes (from -3.98 for Holland to -8.19 for Spain) suggest that process innovation benefits less dramatically from functional diversity compared to other innovation types.** Spain still leads the way in terms of slope (unit impact of CV_FSI on process innovation, *qinpcs*).

Figure 12. Share of Firms Introducing Process Innovations by Functional Diversification

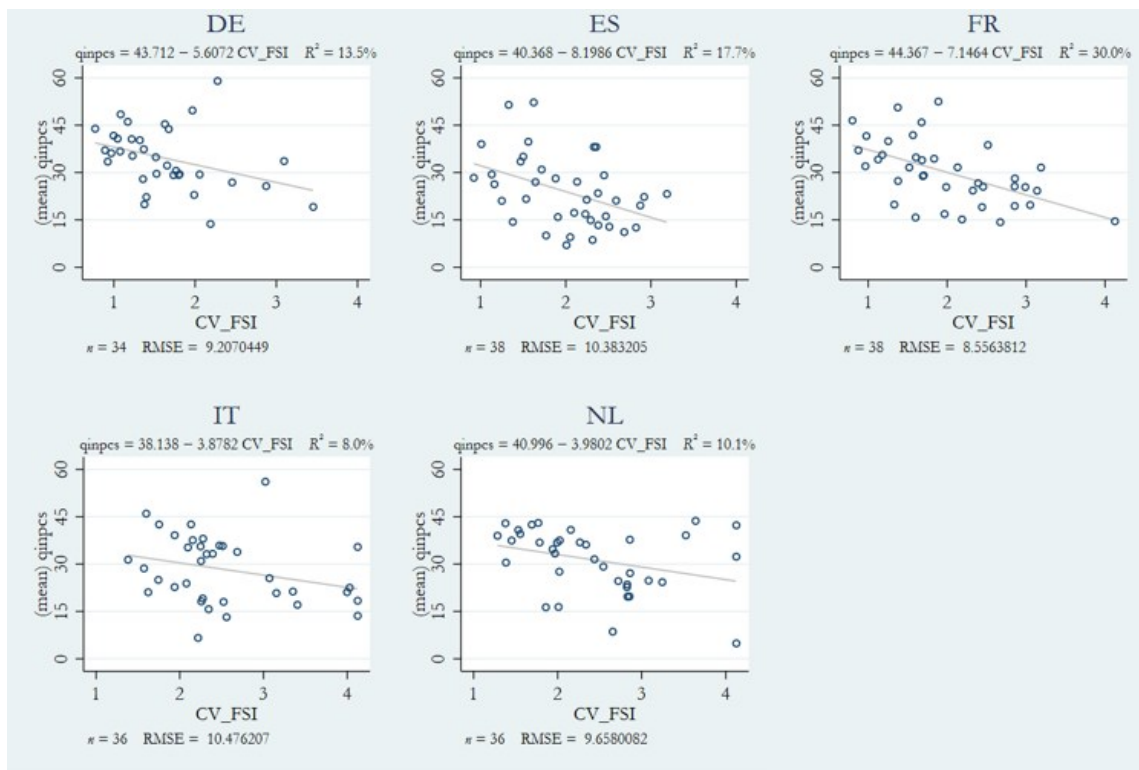
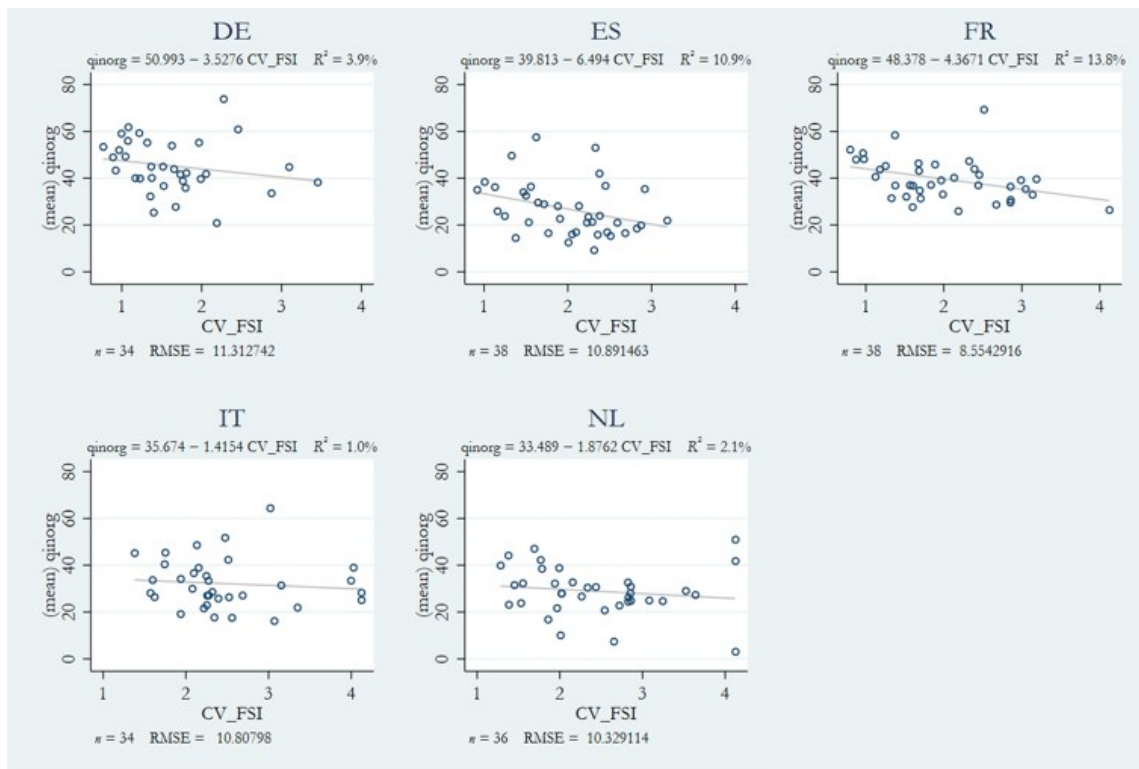


Figure 13. Share of Firms Introducing Organization Innovations by Functional Diversification



As figure 13 (above) shows, despite showing the weakest relationship (R^2 ranging from 1% in Italy to 13.8% in France), the negative slopes still indicate that higher functional diversity promotes organizational innovation. The relatively modest slopes (-1.87 to -6.49) suggest a more subtle but still positive relationship between diversity and organizational innovation capacity.

Overall, the existence of all negative slopes in all plots represent **positive relationships** between functional diversity and innovation. France consistently shows the strongest and most reliable diversity-innovation relationships. Product innovation demonstrates the strongest positive association to increased functional diversity. Higher functional diversity benefits all innovative types, but with varying intensities. The relationship is most pronounced in product innovation and least in organizational innovation. This revised interpretation reveals that functional diversity is **positively associated with** innovation across all measured dimensions and countries. **As the next section will show using econometric analysis, the statistically significant relationship is between functional diversification and product and process, but not organizational, innovation, and only in Services not Manufacturing.**

However, in order to be able to reject the null hypothesis in favor of the alternative hypothesis that functional diversification is associated with higher innovation performances, **we must resolve a major obstacle to this methodology.** Namely, the relationship between CV_FSI and number of Inward FDIs. To determine that the effect of diversification is driving innovation, as hypothesized, we must control for the portion CV_FSI that merely represents the number of inward FDIs. In other words, the lower the number of FDIs entering an industry, the less FDIs there are to spread around for there to be, in the first, place, any meaningful diversification. As such, the higher CV_FSI values likely represent low inward FDIs not concentrated allocations of FDIs.

Taking into account number of FDIs is important, as the way the CV_FSI computation is set up, an industry that receives 1 or 2 FDIs only (just a low FDI recipient) will naturally have a high CV_FSI (low diversification) score, even though it shall fall outside the range of what we are trying to capture, a high concentration of activities by function rather than a lack of activity all together. This is because too few FDIs by definition means too few FDIs to go around all 17 functions.

As a result, we shall apply a series of robustness checks to determine the health of our relationship by controlling for the total FDI by industry variable, “*fdi*.” First, consider that the relationship between diversification and number of FDIs is strong and statistically significant at the highest confidence level, as reported in table 6, below.

Table 6. CV_FSI and FDI Volume Correlation

Variable	Diversification Indicator <i>CV_FSI</i>	Number of observations	Statistical significance $P > t $
Number of Inwards FDIs <i>fdi</i>	-0.527	186	0.000: Statistically significant at the highest possible level

This relationship is represented graphically in Figure 14. A R^2 value of 27.7% indicates that about a quarter of the variation in the CV_FSI (diversification) variable is explained by the variance in the number of inward FDIs, as expected. The slope says that every one additional FDI entering an industry/country decreases CV_FSI (increases the propensity for functional diversity) by 0.003, given an intercept (starting position of 0 FDIs and 2.4 CV_FSI).

Figure 14. General Correlation between Number of Inward FDIs and Diversification

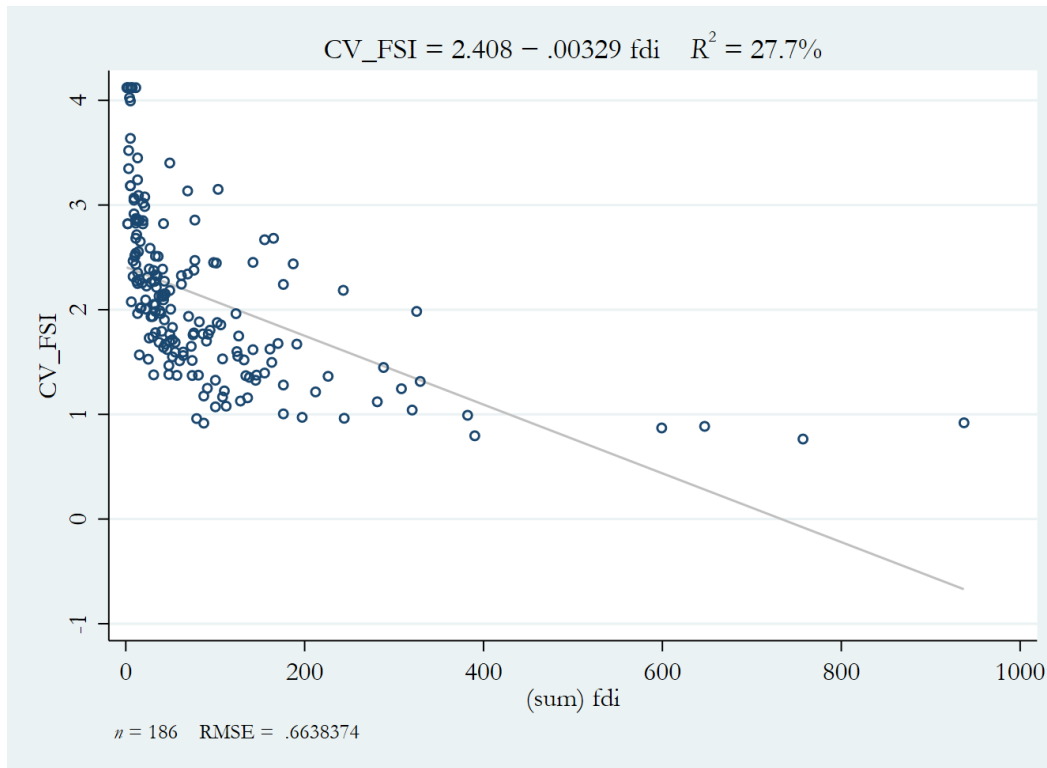
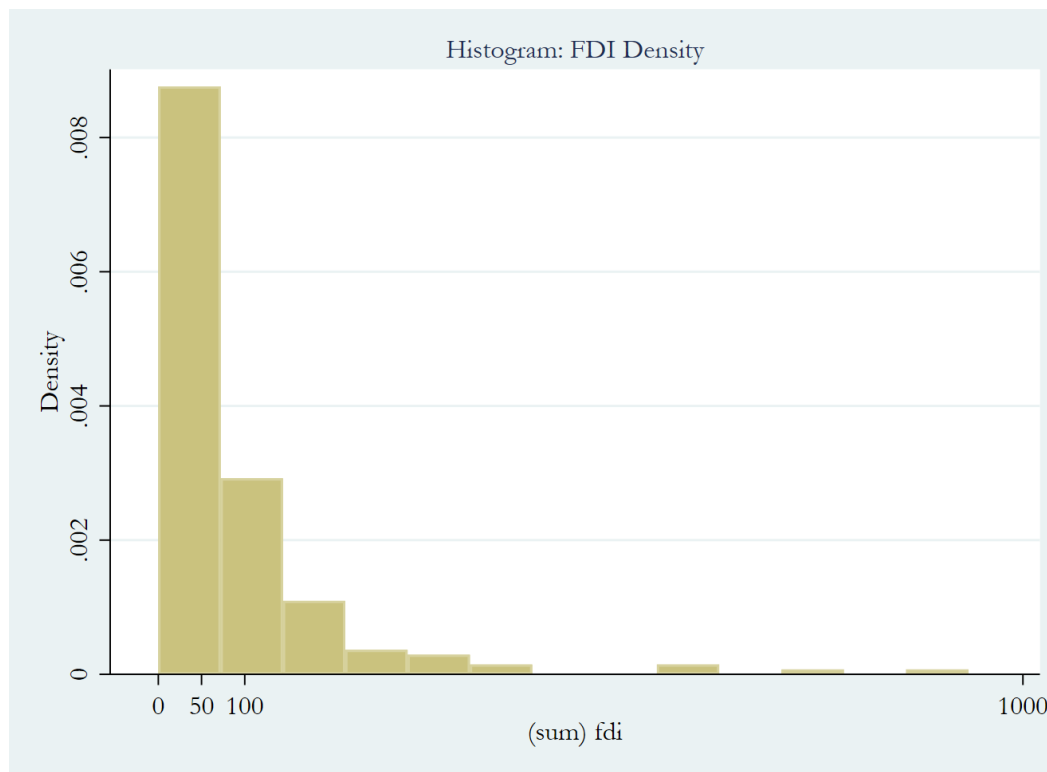


Figure 15. Histogram: Distributional Density of Number of Inward FDI by Industry



A standout feature of Figure 14 (above) concerns the concentration of FDI values (dots) at the lower values of the fdi variable, between 0 & 50, which seem to be where this secondary relationship is most concentrated in power. A clearer depiction of the distribution of FDI is shown in the histogram (above) in Figure 15. Indeed, the concentration of FDI values between 0 and 50 is very high. As such, a closer look at how the primary and secondary relationships behave in this range is critical.

As suspected, the relationship between diversification and number of FDIs is concentrated at particular intervals: the first is around low FDI numbers—albeit the most dense region—namely, below 50 FDIs; and the second is the 8 highest FDI observations (right bound outliers). In total, this constitutes about half of the sample. When sidelined these observations entirely eliminate the possibility that the relationship between CV_FSI and fdi is acting upon the relationship between CV_FSI and the innovation variables. This is shown in the plot below, where 73 observations constitute the sample of perfectly uncorrelated CV_FSI & fdi cases. The range of just below 1 and just over 3 shows indeed almost the entire CV_FSI range:

Figure 16. Correlation between *fdi* and *CV_FSI* in the range 50-250 FDI's

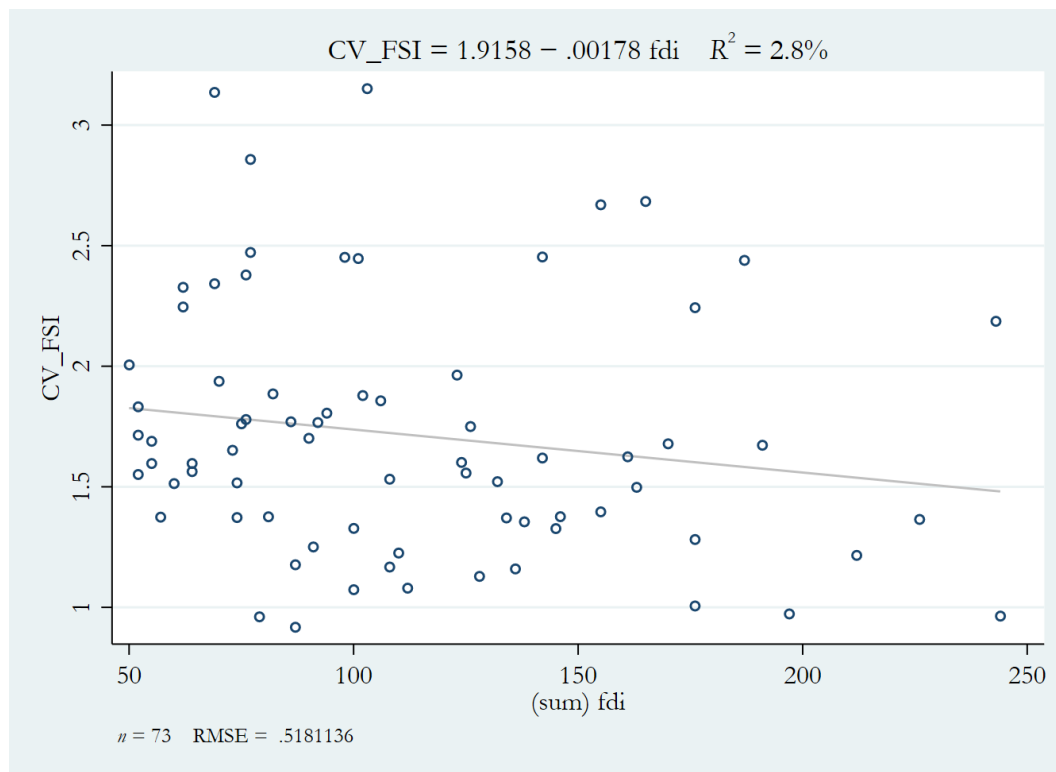


Table 7 shows that within this range ($50 < fdi < 250$)²⁰, the relationship between diversification and number of FDI's show a statistically insignificant correlation of 16%; while within the same range, the correlation involved in the primary relationship between CV_FSI and *qinno* remains highly significant, substantively with a correlation of 46% and statistically significant at the highest (99%) confidence level.²¹

Table 7. Correlations with Diversification Within the 50-250 Inward FDI's Range

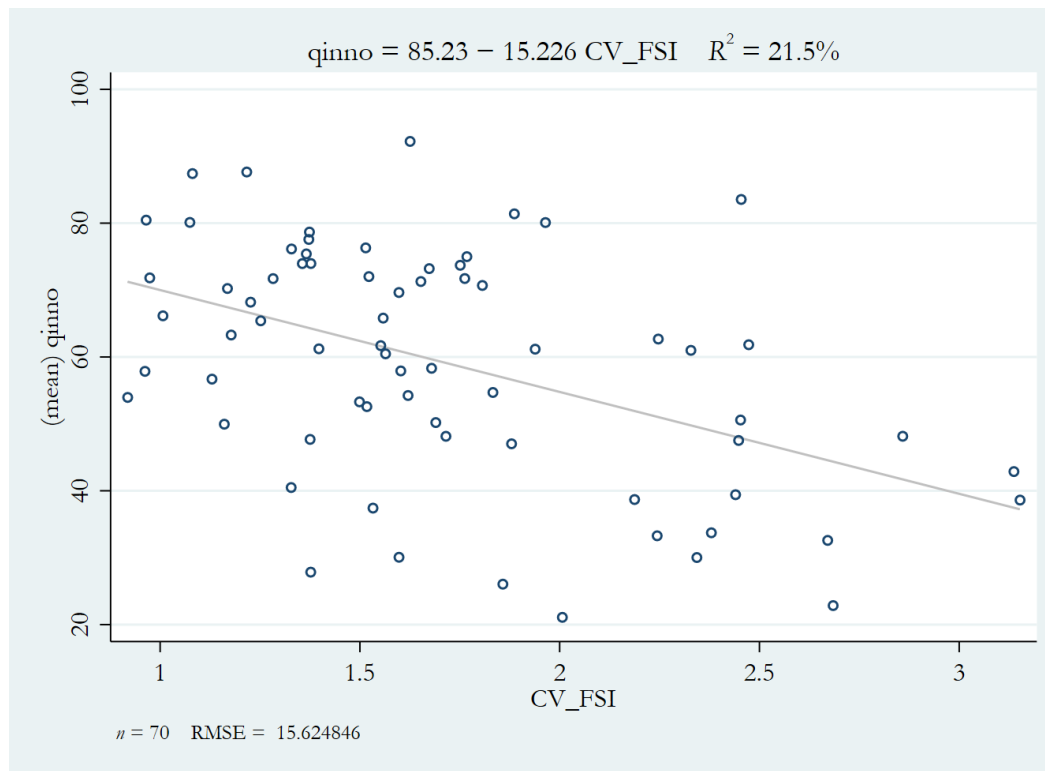
Variable	Correlation with CV_FSI	Number of observations	Statistical significance $P > t $
General Innovation <i>qinno</i>	-0.464	70	0.001: Statistically significant at the highest possible level
Number of Inwards FDI's <i>fdi</i>	-0.167	73	0.159: Statistically <u>insignificant</u> at the highest possible level

²⁰ Please not, the introduction of an upper limit to inward FDI's is to control for outliers on the high side of the spectrum, and, critically, to prevent the dataset from being too highly skewed towards German industries, which disproportionately receive comparatively large numbers of FDI's. The results are mostly the same with or without it.

²¹ Not only that but the relationship between diversification and innovation is much weaker at lower FDI scores, lending further evidence to the idea that the secondary correlation between #FDI's and diversification is not driving the primary correlation between diversification and innovation

Below are the *aaplots* involved in the relationship between functional diversification and general innovativeness within the range of 50-250 FDIs:

Figure 17. Relationship Between Innovation and Diversification in the 50-250 FDIs Range



Within the 50-250 FDIs range, which covers the full range of values in both variables, 70 industry/country pairs exhibit absolutely no relationship between diversification and number of FDIs while maintaining a very strong relationship between diversification and innovation. A R^2 of just above 20% indicates that a fifth of the variation involved in an industry's general innovation (*qinno*) performance can be explained by that same industry's functional diversity. The lowest CV_FSI score of 0.7 is associated with 85% of firms within an industry introducing new general innovations. The slope indicates that every 1 point in the diversification variable is associated with a change of about 15% such that a move from 3 CV_FSI to 2 CV_FSI is associated with an absolute increase in *qinno* of 15% more firms introducing innovations.

The same holds true for all the various types of innovation. In fact, product innovation relationships with diversification become significantly stronger the more the number of FDI extremes are removed from the story. Note also that while this analysis is akin to a simple 1 – variable regression, the overview of variability in the 70 industries involved is such that there is strong representation of all industries, functions, and countries.

3.4.2 | Diversification and Innovation: Simple Regressions with Controls

This section is dedicated to econometrically testing the difference in the relationship between diversification and innovation in manufacturing and service industries. **The simple regressions used here should be interpreted as rigorous correlations with controls instead of fully estimated econometric models.** This is because it is the opinion of this analysis, owing to the complexity described in this chapter and in Chapter 1, that the relationship between innovation and diversification is sophisticated and impacted by omni-present and ever-changing technological regimes, national institutions, and governance linkages that are not easy to quantify. All 3 variables act upon the relationship in heterogenous ways that make model estimation, in the opinion of this author, fraught with difficulty that mar the added benefits of statistical rigor as compared with the controlled correlations presented below.

Specifically, we must consider several attributes of the relationship. A primary concern has to do with the two-way nature of the relationship between the benefits of functional diversification at the industry level and the innovation propensity of that industry. Given that FSI is based on FDI projects, it follows that if **foreign MNEs choose to invest in already innovative industries**, it is the innovativeness that is impacting the FDI location choice (not the other way around), and therefore, reflecting specialization in the indicator, FSI. This fact of endogeneity and circular causality compounds the complexity of the relationship, further disincentivizing strict model estimation.

Standard regression modeling relies on an assumption of exogeneity: independent variables predict a dependent variable in a unidirectional fashion. Because the present system exhibits circular causality where variables simultaneously act as both causes and effects, the assumption of exogeneity is violated. Attempting to force this relationship into a linear regression framework would result in endogeneity bias, yielding mathematically invalid coefficients.

While techniques like Two-Stage Least Squares (2SLS) or Instrumental Variables (IV) can theoretically address endogeneity, they require strictly valid external instruments. Given the high complexity and interconnectedness of this system—compounded by the difficulty of capturing GVC governance, NSI structures, and technological regimes—finding truly exogenous instruments that satisfy the exclusion restriction is practically impossible. Using weak or invalid instruments would introduce more bias than it resolves as compared to the benefits of controlled correlations.

The phenomenon under study is fundamentally characterized by non-linear dynamics (see Chapter 1), multi-layered feedback mechanisms, and emergent behaviors. Therefore, rather than attempting to oversimplify a complex system to fit the rigid constraints of a regression model, we utilized creative and controlled correlations. This approach is natively equipped to map recursive feedback loops and capture systemic complexity without requiring assumptions of linearity or directionality.

Given the discussion in chapter 1 about the a(symmetry) in the characteristics of intangible and tangible knowledge assets, it would follow that due to **non-rivalry and scalability**, knowledge created in one service firm's function—say, marketing analytics or digital process design—can diffuse rapidly across the industry through labour mobility, alliances, and imitation. These spillovers are particularly potent in services, where knowledge is tacit, experiential, and embedded in people and networks rather than in machinery or product blueprints. Functional diversification therefore acts as a sort of multiplier of intangible capital, fostering an industry-wide learning ecosystem that continually regenerates innovation potential. Please note, this does not by any means imply that service industries are supposed to be more innovative, but rather that the diversification-innovation relationship would be more at play in service than manufacturing industries.

In fact, as shown in figure 18, below, the share of firms introducing innovations in the manufacturing sector, aggregated across all time periods, countries, and industries present in the SID and FDI-M merged dataset, **the manufacturing sector consistently commands a higher capacity for innovation than the services sector**. The difference is largest in terms of product innovation where services are associated with an average 20% product innovation compared to the 35% average for manufacturing.

As such, **it is not the difference in base average innovation rates we are interested in, but the capacity of functional diversification to drive innovation**. It would make sense for diversification to form a large part of the determinants of innovation in services, but not in manufacturing. To begin, and before the regression analysis to follow, let us consider the correlations in table 8, below.

In the 50-250 Inward FDI range, which is the area where diversification and volume of FDIs are not correlated, general innovation and diversification are weakly correlated, and that correlation is not statistically significant. The opposite is true, however, in services: in the 50-250 FDIs range, the correlation between general innovation and diversification intensifies, reaching nearly a 50% correlation that is statistically significant at the highest possible level.

In order to identify if this observation is significant or not, it is important to account for more than country and sector differences and FDI volume difference (which is also a proxy—albeit a weak one—for GVC participation). To do this, two variables are redeemed from the SID for the first time in this study: *expinno* (average industry expenditure on innovation) and *ente* (average annual number of enterprises in an industry). Both variables are averages due to the cross-sectional nature of this analysis, however a robustness check was performed where the same regressions below were conducted with these annual figures summed instead of averaged. No significant differences were found.

Figure 18. Average Innovativeness by Sector, Aggregated by Time, Industry, and Country

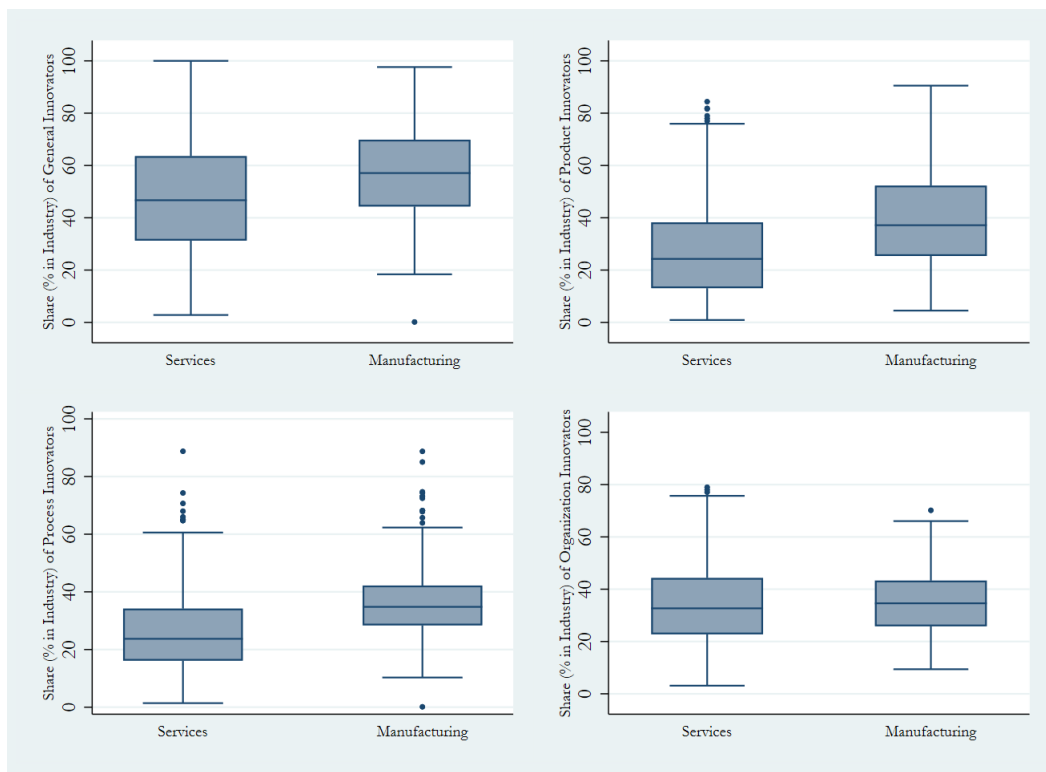


Table 8. Correlation Between Innovation and Diversification by Sector

Innovation Variable	Correlation with CV_FSI	Number of observations	Statistical significance $P > t $
Sector: Manufacturing (Inward FDI Range: ALL)			
General Innovation <i>qinno</i>	-0.481	83	0.000: Statistically insignificant at the highest possible level
Number of Inward FDIs <i>fdi</i>	-0.600	83	0.000: Statistically significant at the highest possible level
Sector: Manufacturing (Inward FDI Range: 50-250)			
General Innovation <i>qinno</i>	-0.221	39	0.177: Statistically insignificant at the highest possible level
Number of Inward FDIs <i>fdi</i>	-0.480	39	0.002: Statistically significant at the highest possible level
Sector: Services (Inward FDI Range: ALL)			

General Innovation <i>qinno</i>	-0.393	99	0.000: Statistically significant at the highest possible level
Number of Inward FDI's <i>fdi</i>	-0.479	103	0.000: Statistically insignificant at the highest possible level
Sector: Services (Inward FDI Range: 50-250)			
General Innovation <i>qinno</i>	-0.468	31	0.008: Statistically significant at the highest possible level
Number of Inward FDI's <i>fdi</i>	-0.007	34	0.970: Statistically insignificant at the highest possible level

The first regression (Table 9) shows without imposing a range in the volume of FDI's, all 4 variables are statistically significant in terms of General Innovation. A coefficient of -5.27 means that every 1 point in industry functional diversification is associated with an increase of around 5% general innovation capacity at the industry level when holding FDI volume, innovation expenditure, and number of enterprises in an industry constant. All of these variables are also significant, and collectively the model accounts for 40% of the variation contained within the *qinno* variable across 179 industry-observations.

When the same regression is given a limit in terms of volume of FDI's of between 50 and 250, the volume of FDI's variable, *fdi*, loses all statistical significance (regression 2 in Table 9). The other control variables remain statistically significant at varying levels, and *CV_FSI* remains statistically significant at the highest confidence level, with an increase of double in terms of its coefficient value. Recalling that in this range the industry diversification score ranges from about 1 to 3, a 1 point change (or additive 33%) increase in diversification score is associated with 10.5% added innovation capacity, which ranges from 10 to 80%, holding the other variables constant. This model also accounts for roughly 40% of the variation observed in general innovativeness.

Given the fact that general innovativeness is an amalgamation of all other innovation types, the same analysis was conducted for all innovation variables present in the sectoral innovation database and, in turn, the community innovation survey. While functional diversification is statistically insignificant for organizational innovation in both the manufacturing and service sectors, process innovation was statistically significant at the 91% confidence level with a coefficient of -2.5²² for service industries yet it was both statistically and substantively highly insignificant for manufacturing industries.

²² Please note that the model with process innovation (*qinpcr*) as the dependent variables is not reported as it shows the exact same trend as with product innovation (*qinpdtr*), which is reported due to the larger coefficient of *CV_FSI* indicating the variable has a stronger effect on that innovation type.

Table 9. Regression Results: Functional Diversification and Innovation Propensity of Industries

Variable	Coefficient	Std. Err.	t	P> t
Reg. 1: General Innovation and Diversification (Observations: 179 ; Adjusted R ² : 0.40)				
Diversification	-5.28	1.62	-3.26	0.001***
FDI	0.02	0.01	2.59	0.010***
Expenditure	0.69	0.00	-3.37	0.000***
# Enterprises	-0.00	0.00	14.27	0.000***
Reg. 2: General Innovation and Diversification in the 250 FDIs Range (Observations: 69 ; Adjusted R ² : 0.35)				
Diversification	-10.50	3.35	-3.13	0.003***
FDI	0.03	0.04	0.92	0.361
Expenditure	0.33	0.19	1.74	0.090*
# Enterprises	-0.00	0.00	-3.03	0.004***
Reg. 3: Product Innovation and Diversification (manufacturing) (Observations: 83; Adjusted R ² : 0.55)				
Diversification	-2.98	2.11	-1.41	0.160
FDI	0.05	0.01	3.90	0.000***
Expenditure	0.52	0.13	4.08	0.000***
# Enterprises	-0.00	0.00	-2.35	0.021**
Reg. 4: Product Innovation and Diversification (services) (Observations: 69 ; Adjusted R ² : 0.35)				
Diversification	-5.30	1.94	-2.73	0.008***
FDI	0.19	0.01	1.58	0.117
Expenditure	1.18	0.24	4.85	0.000***
# Enterprises	-0.00	0.00	6.48	0.002***

As reported in regression 3, product innovation in manufacturing industries does not seem to benefit from functional diversification given the inclusion of FDI volume in the model. Without this latter variable, the CV_FSI indicator showed a statistical significance. However, the inclusion of *fdi* invalidated that. This means that it was never the diversification component of CV_FSI that drove innovation but the spurious correlation between FDI volume and CV_FSI. When that is removed by importing a lower bound limit or by using regression analysis, the relationship between diversification and innovation in Manufacturing is determined to be statistically insignificant.

What is also interesting about this model is the fact that while the CV_FSI variable remains insignificant, the overall model R^2 of $\sim 55\%$, is the highest of all the models attempted in this analysis, including all innovation and sector types and by individual country. As will be elaborated later, this is interpreted to mean that product innovation in manufacturing is perhaps the most standard innovation type with general size and volume variables accounting for the largest variation in it when compared to other combinations by innovation and sector type.

The final regression, 4, shows the same relationship—functional diversity and product innovation—for the services sector. As is the case with process innovation in services, the significant of the CV_FSI indicator is both statistically and substantively favourable. **A CV_FSI coefficient value of -5.30 indicates that a 1-point increase (decrease) in diversification, which ranges from 1 to 3, is associated with a $\sim 5\%$ additive increase (decrease) in product innovativeness in services. This is highly significant due to product innovation in the services sector having one of the lowest averages amongst the other innovation and sector type combinations (see figure 18 above).**

Equally significant is that the FDI volume indicator fell to a statistically insignificant third of its coefficient value when compared to the same model in manufacturing. In this model, all other variables are statistically significant at the highest (99%) possible level. According to an R^2 of 0.45, the whole model accounts for just under half of the variation in product innovativeness of industries in the service sector.

These results are interpreted in terms of the relative relevance of intangible knowledge assets in service industries as compared to their manufacturing counterparts. This can be demonstrated by looking at the number of inward FDIs entering the manufacturing and services sectors in the countries in the dataset—an intuitive FSI. Table 10 reports this:

Table 10. Number of Inward FDIs by Country and Sector

County/Sector	Preproduction FDIs	Production FDIs	Postproduction FDIs
DE Manufacturing	554	957	2572
DE Services	431	87	2155
ES Manufacturing	228	573	465
ES Services	243	57	1151
FR Manufacturing	363	873	745
FR Services	323	53	1491
IT Manufacturing	89	170	241
IT Services	65	54	577
NL Manufacturing	165	154	345
NL Services	218	22	663

As shown in table, and as expected, the number of inward FDIs is skewed by sector type with postproduction FDIs disproportionately going to Services and the number of production FDIs going to Manufacturing. The number of preproduction FDIs is consistent in all countries among both sector types. Given our earlier assertion that the FDI profile of an industry likely reveals its comparative advantage relative to another industry's technological capabilities and factor endowments, the fact that the service (manufacturing) sector is more specialized in postproduction (production) could explain the significant (insignificance) of functional diversity.

Functional diversification enhances innovation performance in services primarily because service sector innovation is, relatively, rooted in **intangible asset accumulation and recombination**. In service industries, value creation depends on intangible assets such as organizational routines, brand reputation, data accumulation, design knowledge, and customer relationships—each deeply embedded in distinct functional domains wherein the functional expertise can be deepened. When industries exhibit high functional diversity, they broaden their collective portfolio of these intangibles, increasing opportunities for novel cross-fertilization of functions.

Recall from earlier that the emergent multiplicity of intangible assets has been studied for at least 75 years (Penrose, 1959). Asset combinations drive service innovation by generating new delivery models, experience-based differentiation, and adaptive business processes. By contrast, manufacturing innovation depends more heavily on tangible capital and codified technological knowledge, where complementarities among functions are narrower and more standardized, muting the marginal benefit of industry-level functional variety. This is indeed shown by the R-Squared value of the model reported in regression 3, wherein standard expenditure, volume, and size explanators account for nearly 60% of all product innovation in Manufacturing. The same model accounts for 45% of the innovation in Services.

Ultimately, the service sector's innovation performance hinges more on the **diversity of its intangible asset base** relative to manufacturing's reliance on capital deepening or physical process optimization. Functional diversification enriches the range of capabilities and knowledge domains circulating within the industry. The resulting increase in IKA variety enhances absorptive capacity and accelerates cumulative learning. In this sense, intangible assets are not merely inputs but the *infrastructure* through which functional diversification translates into superior innovation capacities.

Given these results, we can reject the null hypothesis HC0 in favour of the alternate hypothesis, HC1, confirming that MORE DIVERSIFIED INDUSTRIES ARE ASSOCIATED WITH HIGHER INNOVATION RATES, even when controlling for FDI volume, sector type, expenditure on innovation, and introducing various industry size proxies. What is most interesting is the fact that **this relationship holds only for service industries**. Given that the hypothesis is developed based on an understanding of GVC innovation derived from intangible asset intensity, coupled with the relative specialization of service industries in intangible assets compared to manufacturing (see table 10, above), this result is as expected and hypothesized.

3.5 | Conclusion: Discussion of Key Findings and Limitations

This chapter represents a core of the argument being developed throughout this PhD dissertation—namely, that the functional lens, given its theoretical basis in intangible knowledge asset monopolization, is well suited to capture innovation dynamics absent in product-based positional classifications of industries in GVCs. This argument was developed theoretically and conceptually in chapter 1, with that chapter providing a genealogy of the concept of innovation to determine its most modern form and arguing that that form cannot be captured outside the functional lens. This chapter adds empirical evidence to that discussion by relating a relative functional specialization index of various EU industries to the innovation performance of those industries, showing that indeed the link between functional specialization and innovation in GVCs is statistically and substantively significant.

The limitations and generalisability of these results are discussed in detail in chapter 5, the concluding chapter of this thesis; however, for now, it is important to highlight key limitations of the empirical exercises adopted in this chapter:

- 1) The cross-sectional approach adopted by this chapter does not account for changes over time; it does not account for flows of assets, but only stocks. As admitted by these same pages, intangible and tangible capital assets are asymmetrical in their diffusion, which is an important difference that must be addressed through panel data and a longitudinal study, which is the purpose of the following chapter.
- 2) The time spans of the SID and FDI-M restrict the time span of this study to ending in 2016. This leaves out the last 10 years, which witnessed arguably some of the greatest structural changes in the 21st century given the Covid Pandemic, the acceleration of digital and green technologies, and changing geopolitical landscapes giving rise to an emphasis on functional sovereignty of nations. When FDI-M and the SID, or comparable databases, are extended to include these periods, the analysis must be extended accordingly.
- 3) The countries covered in this study are the 5 largest EU economies by GDP. As such, they represent a highly specific subset of the world's economies, limiting the generalisability of these results to industries of similar nations; Specifically, to nations whose specialization profiles are similar. Importantly, this leaves out developing nations entirely, as well as the Central and Eastern European (CEE) block. Future studies should include CEE countries to have a more representative sample of EU specialization patterns, including production.
- 4) A key limitation has to do with the reliance on FDI volume for the functional specialization index (FSI). An FSI based on the monetary value of those FDIs instead of homogenizing them by the fact of their occurrence (number of projects) might find some different results given that value and number are often inversely correlated: many FDIs can mean lower individual value, and few can mean higher individual value. Future iterations of this work should deflate and convert FDI-M data on the monetary value of FDIs and compute FSI in accordance with SID currency units and deflators. If these works agree with the present one and others that the number of FDIs offer advantages that are lost otherwise, the analysis by monetary terms should still be carried out as a robustness check.

- 5) While the variance explained by the regressions reported in the previous sections are satisfactory for the purposes of this study, a model that accounts for almost all the variance in innovation (90%+) would be required to absolutely determine the link between CV_FSI and the innovation variables. Functional diversification might be capturing residual elements not represented in the models above. Since creating a complete model for industry innovation is not the stated purpose of this study, that falls outside the scope of this work.

Despite these limitations, the findings of this chapter are important contributions to the field, especially as concerns the specialization-innovation nexus. Namely, these contributions and the results they emanate from are as follows:

- 1) The Smile curve hypothesis can be extended from specialization-value nexus only to also specialization-innovation nexus. That is, functions performed in geographically dispersed and functionally fragmented value chains are hierarchically linked not only to profit but also innovation capacities. Industries specialized in preproduction and postproduction functions command consistently higher innovation rates than industries specialized in production functions. Again, it would be interesting to see if these results hold given the introduction of CEE countries into the dataset, as these countries are, in absolute terms—i.e. relative to at least all of Europe—specialized in production functions.
- 2) No general evidence was found that the relationship deepens or weakens given various levels of GVC participation. Some evidence was found for this to be the same in postproduction functions only, but that is considered to be driven by the fact that (see chapter 2) Germany is disproportionally specialized in this functional group and it displays the highest innovation rates across the board as compared to the other countries.
- 3) Functional diversification is linked to higher product and process but not organization innovation performance in the services sector only. Regressions results suggest that manufacturing innovation is mostly driven by standard efficiency- and productivity- based explanators. This is consistent with the ‘low road’ and ‘cost competitive’ strategies often adopted by firms specialized in production, which, relatively, the manufacturing sector is specialized in. This low road cost competition is why production functions are commonly associated with low value capture; conversely, service industries deepen specializations and extract value from their intangible assets through IKA variety.
- 4) Collectively, these results indicate that the functional lens works: given its theoretical foundation in IKA and the monopolization and operationalization of intangibles through ‘rents’, the functional approach represents a way of gauging the returns to specialization accruing to different functions based on their intangible intensity. **The fact the smile curve hypothesis was shown to extend to innovation performance, and that functional diversification is linked to the same in service not manufacturing sectors lends evidence to the strong calibration of this approach** to capture the link between intangible assets and innovation at the industry level in EU countries.

Chapter 3 References

- Ambos, B., Brandl, K., Perri, A., Scalera, V. G., & Van Assche, A. (2021). The Nature of Innovation in Global Value Chains. *Journal of World Business*, 56(6), 1-10. <https://doi.org/10.1016/j.jwb.2021.101221>
- Archibugi, D. & Filippetti, A. (2011). Innovation In Times of Crisis: National Systems of Innovation, Structure, and Demand. *Research Policy*, 40(2), 179-192. <https://doi.org/10.1016/j.respol.2010.09.001>
- Bair, J., & Gereffi, G. (2001). Local Clusters in Global Chains: The Causes and Consequences of Export Dynamism in Turren's Blue Jeans Industry. *World Development*, 29(11), 1885–1903. [https://doi.org/10.1016/S0305-750X\(01\)00075-4](https://doi.org/10.1016/S0305-750X(01)00075-4)
- Balassa, B. (1965). Trade Liberalisation and “Revealed” Comparative Advantage. *The Manchester School*, 33, 99-123. <https://doi.org/10.1111/j.1467-9957.1965.tb00050.x>
- Bi, K., Huang, P. & Wang, X. (2016). Innovation Performance and Influencing Factors of Low-Carbon Technological Innovation Under the Global Value Chain: A Case of Chinese Manufacturing Industry. *Technological Forecasting and Social Change*, 111, 275-284. DOI: 10.1016/j.techfore.2016.07.024
- Buciuni, G. & Pisano, G. (2021). Variety of Innovation in Global Value Chains. *Journal of World Business*, 56(2), 1-13. <https://doi.org/10.1016/j.jwb.2020.101167>
- Caloghirou, Y., Dimas, P., Stamopoulos, D. & Tsakanikas, A. (2022). Intangibles, Innovation, And Sector Specialization in Global Value Chains: A Case Study on the EU's and the UK's Manufacturing Industries. *Technological Forecasting & Social Change*, 177, 2-18. <https://doi.org/10.1016/j.techfore.2022.121488>
- Castellani, D., Jimenez, A. & Zanfei, A. (2013). How Remote are R&D Labs? Distance Factors and International Innovative Activities. *Journal of International Business Studies*, 44, 649–675. DOI:10.1057/jibs.2013.30
- Chen, W., Los, B. & Timmer, M. (2018). Factor Incomes in Global Value Chains: The Role of Intangibles. NBER Working Paper 25242. <http://www.nber.org/papers/w25242>
- Cohendet, P. & Simon, L. (2017). Chapter 3: Concepts and Models of Innovation. In Bathelt, H., Cohendet, P., Henn, S., & Simon, L. *The Elgar Companion to Innovation & Knowledge Creation* (Pp. 33-55). Edward Elgar publishing Cheltenham, UK • Northampton, MA, USA DOI 10.4337/9781782548522
- Corrado, C., Hulten, C., & Sichel, D. (2009). Intangible Capital and U.S. Economic Growth. *Review of Income and Wealth*, 55(3), 661-688. <https://doi.org/10.1111/j.1475-4991.2009.00343.x>
- Coveri, A. & Zanfei, A. (2022). Functional Division of Labour & Value Capture in Global Value : A New Empirical Assessment Based on FDI Data. *Review of International Political Economy*, 30(5), 1984-2011. <https://doi.org/10.1080/09692290.2022.2152074>
- Coveri, A., & Zanfei, A. (2023). The Virtues & Limits of Specialization in [GVCs]: Analysis & Policy Implications. *Journal of Industrial and Business Economics*, 50, 73-90. <https://doi.org/10.1007/s40812-022-00247-9>
- Coveri, A., Paglialunga, E., & Zanfei, A. (2024). Functional Specialization & Upgrading in European Regions: New Insight from FDI Data. Working Paper series 2401, 1-27, University of Urbino Carlo Bo, Department of Economics, Society & Politics
- Crescenzi, R., Pietrobelli, C., & Rabello, R. (2016). Regional strategic assets and the location strategies of emerging countries' multinationals in Europe. *European Planning Studies*, 24(4), 645-667

- De Marchi, V., Di Maria, E., Gulini, R., & Perri, A. (2020). Nurturing International Business Research Through Global Value Chains Literature: A Review and Discussion of Future Research Opportunities. *International Business Review*, 29(5), 1-16.
<https://doi.org/10.1016/j.ibusrev.2020.101708>
- Dedrick, J., Kraemer, K. & Linden, G. (2010). Who Profits From Innovation in Global Value Chains? A study of the iPod and Notebook PCs. *Industrial and Corporate Change*, 19(1), 81-116
- Doan, H-Q., Masciarelli, F. & Meliciani, V. (2024). Intangible Assets, Global Value Chains, and Innovation: Evidence from Vietnamese SMEs. *Industrial and Corporate Change*, 00, 1-29.
DOI:10.1093/icc/dtae011
- Durand, C. & Milberg, W. (2020). Intellectual Monopoly and Global Value Chains. *Review of International Political Economy*, 27(2), 404-429. <https://doi.org/10.1080/09692290.2019.1660703>
- Evangelista, R. & Vazzani, A. (2010). The Economic Impact of Technological and Organizational Innovations. A Firm-Level Analysis. *Research Policy*, 39(10), 1253-1263.
<https://doi.org/10.1016/j.respol.2010.08.004>
- Fagerberg, J., Lundvall, B-A., & Srholecc, M. (2018). Global Value Chains, National Innovation Systems and Economic Development. *The European Journal of Development Research*, 30, 533–556. <https://doi.org/10.1057/s41287-018-0147-2>
- Felice, G. & Tajoli, L. (2018). Global Value Chains Participation and Knowledge Spillovers in Developed and Developing Countries: An Empirical Investigation *The European Journal of Development Research*, 30, 505–532. <https://doi.org/10.1057/s41287-017-0127-y>
- Gallemore, C., Delabre, I., Jespersen, K. & Liu, T. (2022). To See & Be Seen: Technological Change & Power in Deforestation Driving Global Value Chains. *Global networks*, 22(4), 615-630. <https://doi.org/10.1111/glob.12383>
- Gereffi, G. & Frederick, S. (2010). The Global Apparel Value Chain, Trade and the Crisis: Challenges and Opportunities For Developing Countries, 157-208, in Cattaneo, O., Gereffi, G. & Staritz. (2010). Global Value Chains in a Postcrisis World: A Development Perspective. The World Bank
- Haakonsson, S. J., & Slepnirov, D. (2018). Technology Transmission Across National Innovation Systems: The Role of Danish Suppliers in Upgrading the Wind Energy Industry in China. *The European Journal of Development Research*, 30, 462-480.
<https://doi.org/10.1057/s41287-018-0128-5>
- Humphrey, J., Ding, K., Fujita, M., Hioki, S., & Kimura, K. (2018). Platforms, Innovation and Capability Development in the Chinese Domestic Market. *The European Journal of Development Research*, 30, 408–423. <https://doi.org/10.1057/s41287-018-0145-4>
- Humphrey, J. & Schmitz, H. (2002). Developing Country Firms in the World Economy: Governance and Upgrading in Global Value Chains. Output of the joint IDS-INEF Project, 1-36. <http://www.ids.ac.uk/ids/global/vw.html>
- Iizuka, M., & Keijser, C. (2018). Looking Beyond Global Value Chains in Capacity Development: The Case of the IT-Enabled Service (ITES) Sector in South Africa *The European Journal of Development Research*, 30, 442–461. <https://doi.org/10.1057/s41287-017-0110-7>
- Javorcik, B. (2020). Reshaping of Global Supply Chains Will Take Place, But It Will Not Happen Fast. *Journal of Chinese Economic and Business Studies*, 18(4), 321–325.
<https://doi.org/10.1080/14765284.2020.1855051>
- Jurowetzki, R., Lema, R., & Lundvall, B-A. (2018). Combining Innovation Systems and Global Value Chains for Development: Towards a Research Agenda *The European Journal of Development Research*, 30, 364–388. <https://doi.org/10.1057/s41287-018-0137-4>
- Lee, K., Mao, Z., & Szapiro, M. (2018). From Global Value Chains (GVC) to Innovation

- Systems for Local Value Chains and Knowledge Creation. *The European Journal of Development Research*, 30, 424–441. <https://doi.org/10.1057/s41287-017-0111-6>
- Lema, R., Rabellotti, R. & Sampath, P. G. (2018). Innovation Trajectories in Developing Countries: Co-evolution of Global Value Chains and Innovation Systems. *The European Journal of Development Research*, 30, 345–363. <https://doi.org/10.1057/s41287-018-0149-0>
- Malerba, F. (2002). Sectoral Systems of Innovation and Production. *Research Policy*, 31(2), 247–264. [https://doi.org/10.1016/S0048-7333\(01\)00139-1](https://doi.org/10.1016/S0048-7333(01)00139-1)
- Marcolin, L., Miroudot, S. & Squicciarini, M. (2016). Routine Jobs, Employment and Technological Innovation in Global Value Chains. *OECD Science, Technology and Industry Working Papers* 2016/01, OECD Publishing, Paris. <http://dx.doi.org/10.1787/5jm5dcz2d26j-en>
- Montresor, S. & Vezzani, A. (2016). Intangible Investments and Innovation Propensity: Evidence from the Innobarometer 2013. *Industry and Innovation*, 23(4), 331–352. DOI: 10.1080/13662716.2016.1151770
- Morrison, A., Pietrobelli, C., & Rabellotti, R. (2008). Global Value Chains and Technological Capabilities: A Framework to Study Industrial Innovation in Developing Countries. *Oxford Development Studies*, 36(1), 39–58. <http://dx.doi.org/10.1080/13600810701848144>
- Mudambi, R. (2008). Location, Control, and Innovation in Knowledge-Intensive Industries. *Journal of Economic Geography*, 8(5), 699–725. <https://doi.org/10.1093/jeg/lbn024>
- Pagano, U. (2014). The Crisis of Intellectual Monopoly Capitalism. *Cambridge Journal of Economics*, 38(6), 1409–1429. <https://doi.org/10.1093/cje/beu025>
- Penrose, E. (1959). *The Theory of the Growth of the Firm*. New York, NY: John Wiley.
- Pietrobelli, C. & Rabellotti, R. (2011). Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? *World Development*, 39(7), 1261–1269. doi:10.1016/j.worlddev.2010.05.013
- Pietrobelli, C. & Rabellotti, R. (2018). Do Global Value Chains Offer Developing Countries Learning and Innovation Opportunities? *The European Journal of Development Research*, 30, 389–407. <https://doi.org/10.1057/s41287-017-0126-z>
- Pietrobelli, C. & Staritz, C. (2018). Upgrading, Interactive Learning, and Innovation Systems in Value Chain Interventions. *The European Journal of Development Research*, 30, 557–574. <https://doi.org/10.1057/s41287-017-0112-5>
- Pisano, G. & Shih, W. (2012). *Producing Prosperity: Why America Needs a Manufacturing renaissance*. Harvard Business Press.
- Rodrik, D. (2018). New Technologies, Global Value Chains, and Developing Economies. *NBER Working Paper Series*, No. 25164, 1–28. <https://www.nber.org/papers/w25164>
- Sampath, P. G. & Vallejo, B. (2018). Trade, Global Value Chains and Upgrading: What, When and How? *The European Journal of Development Research*, 30, 481–504. <https://doi.org/10.1057/s41287-018-0148-1>
- Serfati, C. (2008). Financial Dimensions of Transnational Corporations, Global Value Chain and Technological Innovation. *Journal of Innovation Economics & Management*, 2(2), 35–61. <https://doi.org/10.3917/jie.002.0035>
- Song, M. & Wang, S. (2017). Participation in Global Value Chains and Green Technology Progress: Evidence from Big Data of Chinese Enterprises. *Environmental science and Pollution Research*, 24, 1648–1661. DOI 10.1007/s11356-016-7925-1
- Stollinger, R. (2021). Testing the Smile Curve: Functional Specialisation and Value Creation in GVCs. *Structural Change and Economic Dynamics*, 56, 93–116. <https://doi.org/10.1016/j.strueco.2020.10.002>
- Sturgeon, T. & Van Biesebroeck, J. (2011). Global Value Chains in the Automotive Industry: an

- Enhanced Role for Developing Countries? *International Journal of Technological Learning, Innovation and Development*, 4(3), 181-205
- Timmer, M., Miroudot, S. & de Vries, G. (2019). Functional Specialisation in Trade. *Journal of Economic Geography*, 19(1), 1–30. <https://doi.org/10.1093/jeg/lby056>
- Van Assche, A. (2017). Chapter 45: Global Value Chains and Innovation. In Bathelt, H., Cohendet, P., Henn, S., & Simon, L. *The Elgar Companion to Innovation & Knowledge Creation* (Pp. 739-751). Edward Elgar publishing Cheltenham, UK • Northampton, MA, USA. DOI: 10.4337/9781782548522
- Veugelers, R. (2016). The European Union's Growing Innovation Divide. *Bruegel Policy Contributions* 13667, Bruegel

Chapter 4 | Functional Upgrading and Innovation Propensity of Industries

4.0 | Executive Summary and Chapter Roadmap

In the previous chapter we examined the cross-sectional relationship between functional positioning of industries in global value chains and innovation capacity. Drawing on FDI Markets data in combination with the Sectoral Innovation Database (SID), we built a dataset of 38 industries across five European economies—Germany, Spain, France, Italy, and the Netherlands—between 2003 and 2016. Cross sectional, quantitative analysis demonstrates, amongst other points, that specialization in intangible-intensive functions is consistently associated with superior innovation outcomes compared to tangible-intensive ones—namely, pre- and post- production functions command higher capacities for innovation than production functions at the firm-²³ and industry- level.

While this can be interpreted as indicting a positive relationship between specialization in intangible intensive functions and innovation capacity, the chapter also suggested, however, that such an investigation, while critical in extending the specialization-value nexus to innovation, is insufficient because it does not measure change. As such, the cross-sectional analysis is incapable of capturing key GVC processes intimately related to innovation, primarily functional upgrading, downgrading, and deepening. In query terms, how are the concepts of upgrading and innovation capacity linked? Is their common conflation as the *same thing* warranted? Do they, at the very least, move in unison? Or, as suggested by some scholars (see section 4.2 below), could functionally favourable structural change (upgrading) impede innovation capacities?

In this chapter, we try to answer these and other questions by reintroducing the time dimension to the SID-FDIM merged dataset across 4 periods (namely, 4, 5, and 6 with 3 as a baseline) between 2003 and 2016. Section 4.1 discusses the theoretical link between innovation and upgrading, recalling the common conflation between the 2, and suggesting a discrete and empirically relevant definition for upgrading based on, but extending beyond, the Evolutionary Economic Geography (EEG) literature. This section draws on the findings of the previous chapter to suggest functional upgrading is better seen as functional ‘entry’ unless a favourable outcome is observed instead of just assumed. The chapter shows that adding specializations in pre- and post- production functions is, in fact, commonly associated with lower or similar innovation rates in the same period. This is in line with the suggestions from the literature also presented in this section.

Section 4.2 identifies patterns of structural change at the function level. This means that between the 4 periods in the data, we will identify instances of functional change in preproduction, production, and postproduction (highest level of functional aggregation as discussed in chapters 2 and 3). In other words, we will report which industry /country pair maintained specialization or nonspecialization between any consecutive periods (SID time structure) and which entered or exited a previously absent specialization.

In this chapter, in addition to functions being smile curve groupings (highly aggregated), so are industries. The Pavitt taxonomy is used to group the 38 industries by Pavitt type to account for industry-fixed effects related to particularities of technological innovation in Science Based (SB), Supplier Dominated (SD), Specialized Supplier (SS), and Scale and Information Intensive (SII) industries. For example, in the case of the latter, SII industries, zero changed is observed in production

²³ Recall that SID innovation statistics are based on CIS, and so the interpretation of the results on both the micro and meso level.

and postproduction specializations in any country. Countries that entered specialized in either of these functions in 2003 maintained that specialization throughout to 2016. Preproduction specializations witnessed some change. For example, relative to the other countries, German SII industries ‘exited’ their upstream specialization in period 4 (2008-2010) and France’s briefly ‘entered’ the specialization in period 5 (2012-2014), after which exiting in period 6 (2014-2016), displaying an overall pattern of oscillation.

Section 4.3 presents observations covering industries by Pavitt groups between 2003 and 2016 in the 5 countries of interest, showing the patterns over time in pre- and post- production specializations from period to period. This section displays one key findings: when the ‘downgrading’ and ‘upgrading’ industries are combined to represent the category of functional change, they perform lower than their functional continuity (continued non/specialization) counterparts. This is most salient in preproduction and product innovativeness, indicating structural change in preproduction specializations causes the greatest disruptions and lowering overall, but especially, product innovation rates.

Finally, section 4.4 concludes. The overall contributions of this chapter are twofold. The first is the need to disentangle between upgrading and deepening, which not only do not mean the same thing, but also sometimes move against each other. The second has to do with the need to discriminate between cross sectional analysis and patterns of change. The fact that intangible knowledge leads to innovation because of intellectual monopoly capitalism is accepted, but there are ‘bumps in the road’ that are relevant for business planning and policy.

4.1 | Introduction

Chapter 3 explored the relationship between Functional Specialization Profiles (FSPs) of European industries and their innovation propensities. Drawing on novel cross-sectional data aggregated at multiple levels, we provided new empirical evidence supporting the "smile curve" hypothesis—that is, functions intensive in intangible assets tend to capture higher levels of innovation than those grounded in tangible activities.

However, an important caveat must be addressed. The dataset underpinning this analysis is limited to five European Union countries, rather than encompassing the global economy. While this comparative sample allows for important insights into European specialization, **it also reveals a structural pattern common across advanced economies: a general lack of specialization in production functions.** Instead, these economies—including the EU member states in our sample, as well as countries like the United States and advanced Asian economies—tend to concentrate their specialization in upstream (e.g. R&D and design) and downstream (e.g. sales and logistics) functions.

This reality exposes a conceptual limitation in the tangible–intangible dichotomy. While the distinction between tangible and intangible functions has proven useful in the context of development studies—particularly when assessing upgrading trajectories in emerging economies—it falls short in capturing the nuanced differences in functional specialization profiles of advanced economies. Indeed, while development remains a central application of the GVC framework and analytical approach, attention is also paid to questions of value capture and innovation within developed contexts (De Marchi et al., 2020).

In lay terms, the tangible–intangible dichotomy allows us to compare preproduction and postproduction on the one hand, and production on the other. This allows us to say that intangible-based functions on either side of the smile curve are good for innovation relative to the tangible-based counterparts: production functions. As such, businesses and industries should aim to change specializations accordingly. This is why entering into a functional specialization in pre- or post-production functions is often immediately called “upgrading.” Simply put, these are the better functions, and performing their related activities is good. **This is problematic as often it occludes the reality of structural change within GVC-participating firms.**

Indeed, “[a] number of recent studies caution that one needs to be careful to avoid painting an overly rosy picture of the link between GVCs and innovation (Pisano and Shih 2009; Fuchs and Kirchain 2010)” (Van Assche, 2017: 745). Indeed, and as documented in detail in chapter 1, this rosiness is partly owed to the conceptual conflation in the terminologies of “innovation” and “upgrading,” conflation that this PhD dissertation has attempted to address directly. While chapters 2 and 3—respectively—have aligned the conceptual definition and empirical measure of ‘innovation’ with dedicated evolutionary scholarship, this chapter does so for the term functional ‘upgrading’.

This form of ‘upgrading’ is particularly important within the family of product, process, functional, and inter-chain upgrading due to the inherent connotation of the hierarchy of functions within GVCs. It is argued while this hierarchy proves true in the specialization–innovation nexus, the process of ‘changing’ functional profiles can leave industries less innovative when compared to the process of ‘deepening’ a functional profile. As such, at least in terms of specialization and innovation, the terms, “upgrading” and “downgrading” should be avoided until the *assumed* normative (favourable or unfavourable) impacts of the change are indeed *observed* and that functional change is better understood in EEG terms of functional “entry” and “exit”—the non-normative counterparts of “upgrading” and “downgrading” respectively.

Sections 4.2 and 4.3 present the data on—respectively—the structural change of European industry and the associated changes in innovativeness. Before that, however, it is important to review what is known in the literature about (1) the connection between innovation and (functional) upgrading and (2) the connection between innovation, function, and industry ‘types’—specifically, the Pavitt and revised Pavitt (Bogliacino & Pianta, 2016) taxonomy ➔

4.1.1 | Functional Upgrading – v – Functional Deepening

Recall from chapter 1 the argument that the concept of upgrading is inconsistently applied as both a synonym and an outcome of innovation, leading to analytical confusion and weak empirical grounding, as studies rarely examine the underlying learning processes, often assuming upgrading whenever positive results appear (Morrison et al., 2008: 45). **The idea of “moving up the value ladder” in value chains oversimplifies upgrading by implying a linear process, overlooking the importance of deepening technological capabilities and exploring new opportunities within the same stage of the value chain** (ibid, 49). This chapter provides empirical support for the nonlinearity of GVCs, as identified by Morrison et al., and echoed by others such as Pietrobelli and Rabellotti (2011) and Van Assche (2017).

This idea has been gaining traction in recent years. According to De Marchi et al. (2020):

The debate on innovation in GVC studies has received less explicit consideration than in other streams of research (Giuliani, De Marchi, & Rabellotti, 2018; Pietrobelli & Rabellotti, 2011), partially because GVC scholars have approached innovation as a component of the concept of upgrading (Morrison et al., 2008). GVC scholars have explored innovation at multiple levels by analysing it within single firms (e.g., a supplier), inter-firm networks, or at the industry (GVC) level. The concept of (economic) upgrading lost relevance in the literature over time (investigated by 21% of papers in the earliest period; 13% in the latest) whereas the attention to innovation increased slightly (De Marchi et al., 2020: 7).

As such, to correct for this conflation of terminology, this present work has attempted in the previous two chapters to advance a conceptual and empirical understanding of innovation as a process of capacity building, measured as a propensity, emanating from firm interactions, in an open system of global production fragmentation. What, then, is functional upgrading? This chapter advances the following definition, theoretically substantiating it throughout the remainder of this section and empirical analysis justifying it in section 4.3:

Functional ‘Upgrading’ implies an observed favourable outcome of positional change undergone by a firm, industry, region, or country within a GVC over time. “Observed” means if (not when) that change is confirmed to directly cause sustained, improvements in GVC position. When no value is captured (yet), it is better to refer to the change without the normative connotation—i.e. functional *entry* instead of functional *upgrading*. Given the understanding and proven hierarchy of functions in GVCs, well documented in this and other works in terms of economic and innovation value.

Functional ‘Deepening’ refers to the persistence and consolidation of a functional specialization across long periods of time, such that the activity becomes embedded in the industry’s capability base rather than appearing as a short-lived entry. While functional change is the hallmark of ‘upgrading’, for ‘deepening’ it is continuity in the face of shock and technological paradigm changes.

Recalling from chapter 1, the balance between continuity and change is at the heart of adapting to evolving technological regimes. Excellence in adapting to a regime means applying known knowledge well but also learning new knowledge. In other words, it is a balancing act “between continuity and change [done] in a competitively effective fashion” (Dosi et al., 2008: 1168). Seen in these terms, the balance between change and continuity is used to explain, for example, why in some instances incumbent industry leaders decline during a ‘paradigm’ change and at other instances they thrive, while at others yet survive but are overtaken in dominance by a new entrant (Dosi et al., 2008: 1175). In this sense, and to return to our conceptual beginning, ‘capability’ refers to the navigation of technological paradigm trajectories with what that entails in terms of the “locality” and “cumulativeness” of learning—it is a capacity, a tendency, a proclivity, or a propensity for effectively managing change and continuity given a dominant technological regime (see Chapter 1).

In the perspective of this study and guided by the results presented in the following sections, this theoretical accounting of balancing continuity and change extends well to the matter of functional upgrading. Even though the literature suggests and our data confirms that some functions better position industries for value capture than others, industries consistently changing their FSP structures, perhaps motivated by industrial strategies and policies at the national level, may be forgoing benefits of ‘strategic deepening’. This is an important yet understudied concept and process in GVC positional change analyses. Perhaps, and as noted by Morrison et al. (2008) in Chapter 1, the idea that GVCs are linear is a dangerous misconception and oversimplification in the literature wherein *upgrading* ‘crowds out’ *deepening* (Morrison et al., 2008: 49).

This idea of a tradeoff between exploring new opportunities and entrenching existing ones goes as far back as Schumpeter’s theory of the firm, yet it is absent from the study of upgrading, especially so to a large degree in quantitative GVC studies. In capturing this dimension, we not only build upon the growing view that **linearity is an inaccurate characteristic of innovation patterns in GVCs**, but also that firm and learning-process heterogeneity are important, and possible to account for in those same studies. Moreover, by creating categories for analyzing change and continuity (deepening and upgrading) in functional specialization, we open up research to study the different stocks and flows, a problem described in [section 1.3](#), and acknowledged as a limitation in chapter 3. This allows us to align the upgrading-innovation relationship with the increasingly loud assertion that learning opportunities in GVCs are not linear nor are they ‘top-down’ (Pietrobelli & Rabellotti, 2011: 1261).

4.1.2| Innovation and the Pavitt Taxonomy (Industry Types)

In addition to reintroducing the time dimension, this Chapter changes the data structure from the previous Chapter 3 in one key manner: the further aggregation of industries by Bogliacino’s and Pianta’s 2016 revised Pavitt (1984) taxonomy. This is done for 3 reasons:

- (1) Added statistical robustness per observation,
- (2) Added “correct[ion] for the bias associated with the subjective nature of question[naires]. The direction of the error is non-systematic across firms in the same industry, filtering out an important source of noise” (Bogliacino & Pianta, 2016: 157); and
- (3) Most importantly, because industry taxonomies are a meaningful way of delineating between observed meso-level heterogeneity in how firms learn ➔

The relationship between innovation patterns and industrial organization emerges distinctly in the Pavitt (1984) taxonomy and its comprehensive reformulation in Pianta and Bogliacino (2016). These frameworks explain not only *how* different industries innovate, but *why they do so*—linking firm-level innovation behavior to common structural characteristics, technological opportunities, and economic functions within GVCs. While Pavitt’s original typology focused on Manufacturing, Pianta and Bogliacino (2016) extend the model to include Services, including the absorption of information-intensive sectors into scale intensive industries to make Scale and Information Intensive (SII) industries.

Science-Based Industries (SB)

Science-based industries, such as pharmaceuticals, electronics, and ICT, draw their core competencies from primary scientific research and R&D knowledge, often produced internally in laboratories or absorbed from public and private research institutions (Pavitt, 1984). Innovation in this group is dominated by breakthrough product innovations, which open new markets and underpin technological competitiveness rather than increased productivity or cost reduction (Pianta & Bogliacino, 2016: 163). These industries exhibit high R&D intensity, a constant drive to exploit emerging scientific opportunities, and a strong complementarity between science and production.

Specialized Suppliers (SS)

Specialized suppliers, which include firms producing capital goods and technical business services, innovate through interaction with users (buyers) rather than purely internal R&D and innovation efforts. Product innovation predominates, but it is driven by learning-by-doing incremental technical refinement. Firms range in size, are highly skilled, and rely on user-producer feedback loops, which make innovation flexible, highly customized, and confined within technological niches.

Scale and Information-Intensive Industries (SII)

The Scale Intensive category in Pavitt’s original classification encompassed industries characterized by economies of scale, for example automotive and metal industries. These commonly display dual innovation patterns: incremental process innovation and occasional product renewal (Pavitt, 1984). Pianta and Bogliacino merge these with information-intensive services—finance, logistics, transportation, and ICT networks—into the new Scale and Information Intensive (SII) class (Pianta & Bogliacino, 2016: 159).

In SII industries, innovation is typically process-oriented, aimed at improving efficiency and reducing costs but also integrating complex information systems. These firms rely on machinery expenditure per employee, automation, and ICT-mediated organizational change (Pianta & Bogliacino, 2016: 166, Table 4). Innovation is thus a means to consolidate organizational routines through technological systems rather than radical new products.

Supplier-Dominated Industries (SD)

Supplier-dominated industries include traditional manufacturing (textiles, food, furniture) and low-tech services (retail, transport, hospitality). These industries typically show minimal internal R&D. Their innovation capacity depends on the technological inputs from upstream producers: for example, capital goods and ICT tools. Their primary strategy is adoption, not generation—i.e. innovation enters through supplier linkages.

4.2| Change and Continuity in FSPs of EU Industries

This section documents patterns over time in functional specialization in the 4 Pavitt groups of industry across Germany, Spain, France, Italy, and the Netherlands between 2003 and 2016—i.e. periods 3 to 6 of the FDI-SID merged dataset. Recall the time structure is set in the following manner:

Period 3²⁴ covers the range of years, 2003 – 2005

Period 4 covers the range of years, 2008 - 2010

Period 5 covers the range of years, 2012 - 2014

Period 6 covers the range of years, 2014 – 2016

Table 1, below, reports the patterns of functional specialization change of industries by the four revised Pavitt groups: Science Based (SB); Supplier Dominated (SD); Specialized Supplier (SS); and Scale and Information Intensive (SII) industries. To arrive at this information, the inward FDI based functional specialization Balassa (1965) index change is computed for every function as in Chapter 3 and the changes from one period to the next show various instructive patterns. **In the following section, the shorter-term patterns (between individual consecutive periods not across all 3) are examined, while in this section the longer-term patterns (across all periods) are presented and analyzed.** Across all industry-Pavitt types and functional specializations, 5 patterns are observed:

Stasis is the pattern of entering period 4 (2008) unspecialized and remaining so until period 6 (2016)

Entrenchment is the pattern of entering period 4 specialized and remaining so until period 6²⁵

Oscillation is the pattern of repeatedly entering and exiting a specialization between periods 4 and 6²⁶

Despecialization is the pattern of exiting a specialization without respecializing in a subsequent period

Specialization is the pattern of entering a specialization without despecializing in a subsequent period

For example, Italy's SB industries witnessed significance change between 2003 and 2016: preproduction specialization saw functional 'entry', meaning a change from *specialization*<1 to *specialization*>1 in the Balassa index was witnessed, wherein, **relative to the population of all countries' SB industries**, Italy gained specialization in preproduction functions; in production, Italy's SB industries tend to oscillate between entering and exiting the specializations; while in the same time Italian SB industries witnessed despecialization from postproduction functions.

²⁴ Period 3 is a baseline period (no observations of change) since there are no FDI observations for P2 as FDI Markets begins in 2003.

²⁵ 'Entrenchment' and 'deepening' are synonyms; this observed pattern is particularly important for the present argument

²⁶ Industries tagged with 'oscillation' in table 1 are industries that between period 4 and period 6 registered one or more entries and one or more exits (eg. P3-P4: entry, P4-P5: exit, P5-P6: entry).

Table 1. Patterns of Functional Change and Continuity in EU Economies, 2003 and 2016

FSP Pattern	Definition	Upstream	Midstream	Downstream	All Specializations
Stasis	Continued non-specialization across all 3 periods	SB-DE SD-DE SS-IT SII-IT	SB-DE SB-NL SD-NL SS-ES SS-NL SII-DE SII-IT SII-NL	SB-ES SB-FR SS-FR SII-ES SII-FR	17 Industries
Entrenchment	Continued specialization across all 3 periods	SB-NL SD-NL SS-ES SS-NL SII-NL	SB-ES SB-FR SS-FR SII-ES SII-FR	SB-DE SS-IT SS-NL SII-DE SII-IT SII-NL	16 Industries
Oscillation	Gain and loss of specialization in any order (both exit and entry happen at least once)	SB-ES SD-ES SD-FR SS-FR SII-ES SII-FR	SB-IT SD-IT SS-DE	SD-ES SD-IT SS-DE SS-ES	13 Industries
Despecialization	Loss of specialization without subsequent regain	SB-FR SS-DE SII-DE	SD-DE SD-ES	SB-IT SB-NL SD-FR SD-NL	9 Industries
Specialization	Gain of specialization without subsequent loss	SB-IT SD-IT	SD-FR SS-IT	SD-DE	5 Industries

4.2.1 | "Factory" Entrenchment: Spain and France's Midstream Hyper Specialization

Initially, it was the intention of this chapter to report the changes in production specializations for completeness only, without significant analysis, as this chapter's focus is on 'upgrading', which means pre- and post- production functions. **That said, the pattern is quite indicative and merits a discussion** in support of and to further explore the last Chapter's findings:

Only 2 industries gained midstream **specializations** and 2 **despecialized**. 5 industries (all Spanish and French) **entrenched** their specialization in production and 8 remained in **stasis**, having never been specialized in production throughout 2003-2016 (mostly German and Dutch industries). Finally, 3 industries **oscillated** between despecializing and respecializing, mostly Italian industries.

The indicator of specialization, **FSI**, is a **relative specialization index based on Balassa (1965)**. **This means that the same industry across different countries cannot all specialise, nor can they all despecialize. If one industry becomes specialised, there must be at least one other industry of the same Pavitt group in another country that becomes despecialized. As such, the patterns documented here can be interpreted comparatively. This is a strength of the empirical strategy adopted.**

First is the timeline of the continued shift of geographic location of production activities from Western Europe to the Mediterranean region. This is especially true in Science Based and Scale and Information Intensive industries, wherein Germany and the Netherlands lost their specializations in production functions to their Spanish and French counterparts. Consider the patterns of specialization for the 8 ES and FR industry types in the **'Midstream'** column in Table 1 above:

The 'Entrenchment' pattern is entirely dominated by Spanish and French industries (SB-ES, SB-FR, SS-FR, SII-ES, SII-FR). **No other industry in any other country in the data entrenched its production specialization.** Of the remaining 3 industries only 1 (SS-ES) remained unspecialized (stasis) in production all throughout. This is as opposed to 3 NL, 2 DE, and 1 IT industries in stasis. Finally, SD-ES lost its production specialization to SD-FR. The pattern is clear: Spain and France are 'deepening' their specialization in production functions over time, but against a Europe that is shifting away from the 'factory' to the 'logistics hub' type FSP across industries. The over-time analysis confirms aspects of our past results from Chapter 3. More importantly, however, it clarifies details about the mechanisms of action and implications at play.

Specifically, given what we know from previous discussions along these pages, this shift in production geography within the European economy implies a (un)favorable positional move for Western Europe (the Mediterranean region). This is not a novel proposition; however, it does raise an important addendum to our previous observations: recalling figure 4 from Chapter 2 (repeated below as figure 1 for convenience), the only country increasing its annual FDI volume in production functions is Germany. This is indicated by the slope of the line of fit in figure 1. Based on the above analysis, we can deepen our interpretation of this trend:

(1) Germany's disproportionate increase in production FDIs (in absolute terms) over time is owed to its generally strong performance in attracting FDIs across all functions. In fact, given the results above using the FSI indicator at the highest functional level of aggregation, Germany has lost its production specialization over time to Spain and France.

Figure 1. Number of Inwards FDIs in Production Functions Over Time



(2) Spain and France are heavily specialized in production functions, much more so than initially thought given a first glance at the figure above, which was first introduced in Chapter 2. Consider the non-linear pattern: in both countries, between 2003 and 2009, there is a clear annual increase in production-related FDIs (this is not the case in Italy or Holland). The Financial Collapse years mark a massive fall off in the number of production-related FDI projects entering both countries (and DE). However, that lull was short lived; the pattern of increase continues again immediately after (in FR around 2012, and in ES around 2015). As such, even though ‘factory’ specializations in Europe, overall and relative to other specializations (even within ES and FR), are declining, there is reason to believe that, especially in SB and SII industries, Spain and France are maintaining and deepening a production specialization.

(3) **Spain and France are displaying early evidence of hyper specialization.** Given the latter point, it is prudent to ask if this deepening of production specialization is occurring simultaneously as loss of or persistent unspecialization in upstream and downstream functional positions. The answer is a clear yes: consider the highlighted portions in table 1. The similarity between Spanish and French SB and SII industries is near perfect: both SB-ES and SB-FR, as well as SII-ES and SII-FR, present a pattern of stasis in terms of their downstream specialization pattern between 2003 and 2016. In fact, together with SS-FR, these are the only five industries that show the pattern of stasis in postproduction functional specialization. The remaining three industries either oscillated (SD-ES, SS-ES) or despecialized (SD-FR) in postproduction. Similarly, in terms of upstream functional change, the lack of specialization remains a similarity shared by ES and FR industries: 6 of the 8 industries are in a pattern of oscillation, with the remaining 2 despecializing (SB-FR) and entrenching (SS-ES). **This**

latter industry, SS-ES, represents the single exception of an instance of intangible-intensive specialization held all throughout the panel dataset by a Spanish or a French industry.

In conclusion, Spain and France are increasingly acting as "Europe's factories," even as the continent generally shifts away from this model.. This entrenchment reflects a deepening of specialization model in the **Scale & Information Intensive (SII)** and **Science Based (SB)** that could create problems for Mediterranean countries of Europe. According to Pavitt (1984), SII industries (like vehicles and metals) rely on large-scale production and process innovation to maintain competitiveness. The fact that Spain and France are "entrenching" here suggests they are capturing the **learning-by-doing** and **learning-by-using** advantages associated with process technology that, particularly, Germany is increasingly hollowing out in favor of downstream activities. Bogliacino & Pianta (2016) note that for these sectors, innovation is often labor-saving and focused on cost-cutting. By becoming the "factories," Spain and France are not merely performing low-value work; they are anchoring the **technological trajectories** of sectors where process efficiency is the primary innovation driver, making this move unfavorable relative to the higher-value "logistics hub" model seen in Germany where innovation opportunities presented by SII and SB industries are better exploited.

4.2.2| Resilience and Flux: The Opposite Patterns in SII and SD Industry Types

As noted above, production function specializations are not the subject of this chapter. Instead, the goal is to examine the innovation propensities associated with gaining or losing a high-value (non-midstream) specialization. As such, the first step is to describe the instances of 'change' and 'continuity' in the data. As can be seen from table 1, above, there are far greater instances of continuity than change across all industry types. Instances of functional despecialization and specialization represent instances of change (14 total), and they are greatest in SD industries (7 industries), followed by SB (4), then SS (2); only 1 SII industry witnessed any meaningful change in specialization (Germany's SII industries despecialized from Upstream functions). This means that SII industries in Europe witnessed absolutely no changes in production and postproduction functions in the period under examination, with preproduction specialization witnessing the one change of SII-DE.

This points to interesting questions concerning the causes and consequences of structural change (in the case of SD) and continuity (in the case of SII). Further motivating these questions is the striking lack of instances of entrenchment or stasis in SD industries. In terms of the latter (SD), all industry-Pavitt types are almost equally represented, except for supplier dominated industries, which show only 1 instance of stasis (Germany) and 1 instance of entrenchment (Netherlands). Moreover, these are explainable as exceptions. Germany (Holland) is uniquely specialized in Support (Headquarter) services (see previous two chapters as well as the following discussion). As such, a dominant and loud trend from the above is the perpetual flux of SD industries in terms of the geographic locations of value chain functions.

This is also backed up by the fact that within the oscillation functional pattern, supplier dominated industries are extremely overrepresented as opposed to the average: 6 out of the 13 industry specialization patterns tagged with oscillation are supplier dominated industry specializations—almost half. A further interesting point is that in terms of SD as well as the other Pavitt-industries' specializations, oscillation seems to only be a Mediterranean region phenomenon. No Dutch industries, and only 2 German ones, display that pattern. This is contrast to 3 Italian, 3 French, and 5 Spanish industry specializations presenting with a pattern of 'oscillation'.

Given the differences in innovation patterns between industry types, we can infer from the revised Pavitt taxonomy some additional interpretations of these findings, the most important of which is that related to SD industries. These are the least internally innovative group in Pavitt's original scheme. They rely heavily on machinery, equipment, and inputs developed elsewhere, and their innovation is usually introduced through suppliers rather than internal RD. Bogliacino and Pianta keep that core definition and place wholesale, retail, transport, hospitality, and other traditional sectors in this class because the data show low internal innovative intensity and weak RD content. The revised evidence also shows that SD sectors remain the weakest in innovation intensity across the classes, although they can still vary in process innovation and demand response.

That makes the observed entry-and-exit behavior in SD especially important. A temporary specialization in an SD industry does not necessarily mean durable upgrading; it may simply reflect a short-lived capability to absorb external knowledge, exploit a market window, or perform a task that is not sustained once external conditions change. The fact that Italy, Spain, and France often enter and exit those positions is therefore best read as a relative distribution of functional control, not as instances of upgrading or downgrading or any normatively loaded term. h

Conversely, Change in SII would imply gain of knowledge given the industry's much more rigid barriers to entry in terms of capital and knowledge assets. As will be shown shortly, these changes, however, do not occur. SII structural evolution patterns across Europe indicate positional permanence and stiff barriers not only to entry, but also to exit.

4.2.2| The "Logistics Hub" Monopoly: Germany's Postproduction Dominance

Looking at individual period changes, the story of the changing SD industry FSPs becomes clearer: in period 3 (2003-2005), prior to the 2008 Financial Collapse, German SD industries were unspecialized in postproduction functions relative to a population that includes French and Dutch SD industries, which showed strong specialization in downstream functions. However, **both France and the Netherlands lost their postproduction specializations to Germany**, the former in period 4 and the latter in period 5. Neither was able to regain it. Italian and Spanish SD industries also attempted postproduction specialization entries in periods 4 and 5 respectively, both also exiting the very next period without regaining the specialization. Given these findings, we can determine that in terms of postproduction, the more meaningful **a functional change that occurred was in German SD industries, which were able to secure monopoly** (in terms of this population of 5 countries) over the specialization. **By 2016, no SD industry group in the dataset remained specialized in downstream functions aside from Germany's.**

A similar pattern emerges in German science-based industries, which maintained and deepened its relative specialization in postproduction functions throughout the entire time span of the dataset. The only 2 other countries that, at any point, showed downstream specializations were Italy and Netherlands. Respectively, both exited their specialization in periods 6 and 4. This means that in postproduction **German SB industries have seemingly long held monopoly over this function and, as such, the type of intangible knowledge associated with postproduction functions. This includes marketing knowledge in the form of analytical software and other digital capital, Customer Relationship Management (CRM), data related to marketing and advertising, organizational know-how in large scale logistics and transport, and customer relationship capital. German SB industries can be said to be deepening their expertise in these areas, greatly so since the data began with this pattern already.**

Germany displays a clear pattern of downstream specialization, as suggested from the previous chapter, 3. In fact, only one German industry type, SS, was ever briefly specialized in preproduction functions. At around the time of the Financial Collapse (2008-2010), German SS industries despecialized from upstream functions and have since begun to oscillate between gaining and losing their postproduction specialization. **The other industries are all firmly specialized in postproduction functions, with supplier dominated industries being the latest part of the economy to join the national specialization pattern. SB and SII industries display a pattern of entrenchment in their specialization profile, changing very little over the years.**

Spain and France show the opposite pattern, where any instances of postproduction specialization were lost relative to Germany, and to a lesser extent Italy. The difference between France and Spain is that the latter was able to maintain its specialization in preproduction while the former generally exited preproduction specializations in the latter years. The Netherlands, as expected, shows zero instances of change out of all the countries with one exception: SB and SD Dutch industries despecializing from postproduction (losing the specialization to Germany as just described above). Aside from that, Dutch industries perfectly maintained full specialization in preproduction functions across all Pavitt types, as well as stasis in production across all groups as well. As we know from the previous chapter, this is generally owing to Holland's disproportionate specialization in HQ not R&D related (RDR) functions²⁷. The opposite of this pattern is Italy's case, which shows the largest instances of change across all industry types, skewed more towards a combination of production and postproduction functions.

In conclusion, Germany has secured a near-monopoly over postproduction (downstream) specializations, particularly in **Science-Based (SB)** and **Supplier Dominated (SD)** industries, while other countries like Italy and the Netherlands have largely exited or failed to maintain these positions. Germany's dominance in postproduction reflects a strategic shift towards **service integration** as a core strategy. In the revised Pavitt taxonomy, SB and SD industries increasingly rely on **service-related knowledge**—such as marketing, design, and e-commerce—to renew their competitive advantage. For SB industries, this represents a move beyond the "intellectual monopoly" of R&D (preproduction) into the **intellectual monopoly of the market interface** (postproduction). Germany is not just "upgrading" in the linear sense; it is **deepening its specialization** in the functions that Pavitt identified as being dominated by large firms with the capacity to internalize diverse technological inputs. The exit of Italy and the Netherlands from these specializations suggests they are losing the **organizational know-how** and **digital capital** (CRM, logistics data) that Germany is successfully anchoring as a "stability premium." At least, that may be the case for Italy; Holland demonstrates the clearest pattern of functional diversification and simultaneous deepening in HQ functions, as the next section will show.

4.2.3 | 'Tilt Pattern' Towards National Specialization: Germany and Holland

Recall from [section 1.4](#) that a central insight emerging from the literature is that governance in Global Value Chains (GVCs) is inherently dynamic, shaped by evolving constellations of firms, institutions, and technological change. Power within these chains is not confined to vertical relationships of lead firm dominance; it is also exercised horizontally through the distribution, circulation, and control of knowledge across firms, regions, and industries. Crucially, the characteristics of knowledge itself—its degree of codifiability, its tacit complexity, and its economic significance—play a decisive role in

²⁷ Recall from the previous chapter that RDR and HQ are the two 'narrow' groupings of function that collectively make up the 'broad' grouping called 'upstream' or 'preproduction'.

determining both value capture and the scope for upgrading. In this context, functional upgrading, widely recognized as a consequential pathway to sustained value capture, is neither automatic nor evenly accessible. Rather, it is frequently and deliberately constrained by lead and other firms seeking to preserve their control over high-value, intangible knowledge assets.

Yet, this monopolization of knowledge is not absolute. An increasingly prominent strand of the literature highlights the capacity of local conditions—particularly the presence of robust innovation capabilities, functional diversity, and inter-firm complementarities—to mitigate and, in some cases, partially overcome these asymmetries of power. In this regard, the abundance and relatedness of complex functions within a given regional or industrial ecosystem emerge as critical, though still underexplored, determinants of upgrading trajectories. These factors shape not only the opportunities available to firms but also their ability to learn, recombine knowledge, and gradually penetrate higher-value segments of the chain.

In the context of industrial FSPs, it is argued this theoretical premise is at play—namely, industries in countries with a clear intangible national specialization tilt (eg. HQ in NL or SP in DE) are more easily entering and entrenching their specialization in that function.

Consider Table 2, below, which is a subset of Table 1 showing only long-term German and Dutch industry specialization patterns. The pattern is a clear move towards, and thus consolidating, the national specialization pattern. In the case of Germany, this is downstream specialization. Germany began (2003-2005) with half of its industries (SII and SS) specialized in upstream and downstream functions at the same time. SII-DE despecialized in period 4 (2008-2010) during the Financial Collapse years, and SS in period 5 (2012-2014), in the crisis's aftermath. All German industries ended period 6 (2016) downstream specialized, including SS despite exiting and then reentering (hence the associated designation of 'oscillation' in SS-DE's 'FSP Pattern') the functional position in period 6.

The Netherlands displays the same pattern but in line with its national specialization *tilt* (upstream). All Dutch industries entered the period with complete upstream specialization and maintained it all throughout to the end of period 6. However, initially, it was also much more diversified in its functional profile across industries. In fact, in period 3-4, Dutch industries were all specialized in downstream functions relative to the rest of Europe—the same as Germany. However, the early-mid 2000s (periods 3-4) saw SB-NL despecialize and, in period 5, Dutch supplier dominated (SD) industries followed suit, ending the national dual specialization pattern upheld now by only half of the economy (SII and SS industries). Significantly, despite this, the Netherlands maintains a significantly more diversified national functional profile than Germany, whilst also deepening its national FSP pattern tilted towards upstream specializations.

Table 2. Patterns of Functional Change and Continuity in Germany & Holland, 2003 - 2016

FSP Pattern	Upstream	Downstream
Stasis	SB-DE SD-DE	
Entrenchment	SB-NL SD-NL SS-NL SII-NL	SB-DE SS-NL SII-DE SII-NL
Oscillation		SS-DE
Despecialization	SS-DE SII-DE	SB-NL SD-NL
Specialization		SD-DE

We are calling this a ‘tilt pattern’ following the *smile tilt* hypothesis proposed in the previous chapter. While the hypothesis makes claims about the innovation propensity of industries based on how well they conform to the functional profile of the whole nation, the present argument does not. Instead, it seeks to provide evidence for the underlying pattern motivating the argument: the idea that, over time, industries in the most advanced European Economies are increasing specializing according to the national *tilt*, in the case of NL (DE) towards preproduction (postproduction) functions. More specifically, these national patterns are driven by specific ‘narrow’ function groups not the ‘broad’ ones. If we look under the proverbial hood, we notice that in Germany (Holland), patterns of change over time converge towards ‘support’ (‘HQ’) functions instead of their ‘logistics’ (R&D) counterparts in the downstream (upstream) group.

Specifically, all German ended period 6 with strong specializations in support functions (narrow functional group—see previous chapter), including SB-DE, which began period 3 unspecialized in support functions and SS-DE, which initially barely qualified the cutoff ($FSI > 1$) for specialization. In logistics, however, which collectively with ‘support’ forms the ‘downstream’ group, German industries display erratic specialization patterns: SB oscillates; SD and SII have never gained the specialization; and SS industries unspecialized in period 4 without regaining the specialization in periods 5 or 6.

Again, the Netherlands displays the same pattern but in line with its ‘narrow’ specialization *tilt* (HQ functions). All Dutch industries end period 6 specialized in headquarter functions, including SD and SS, which began unspecialized. However, in terms of RDR functions (R&D-related narrow functional group) Dutch SB and SII industries remained in stasis, never gaining the RDR specialization between 2003 and 2016; SS industries despecialized in period 4 (2006-2008) and SD industries specialized in RDR functions in the same period. To further outline the consistency of this discrepancy between

RDR and HQ functions in Holland, the specialization values of the FSI indicators for HQ in Holland are the highest in the dataset (across all countries and periods and all permutations of the data performed), consistently exceeding a FSI value of 2.0, indicating extreme specialization. This is true of all 4 industry types except for SS industries, which only recently (period 6) increased from a FSI value of just over 1 to a value of 1.9 (Period 6 SS-NL FSI value in HQ).

Given the previous Chapter's results concerning diversification, it would be prudent to monitor the specialization profiles of these industries against what is known about the merits of diversification and limits of hyper specialization (Coveri and Zanfei, 2023), as well as what has been suggested along these pages concerning the pattern of industry tilt towards the national profile, culminating in examining the *Smile Tilt* hypothesis proposed by Chapter 3 that industries in line with the national tilt experience higher returns to specialization. This would require expanding the geographic focus of the dataset to include other countries so as to make generalizable and absolute rather than Europe-centric and relative claims about FSP patterns and their link to innovation.

4.3 | The Paradox of Progress in Upgrading and Innovation

This brief section is concerned with examining functional specialization changes in a framework restricted to 1 period changes (table 1 presented patterns based on behavior over 3 periods), both in terms of innovation change and functional change of industries. That is, whether a change was maintained for more than 1 period consecutively or is oscillating is not considered. Instead, for parsimony and comparability, each inter-period observation is considered standalone and comparable with the others. This is an important caveat and limitations in the following empirical exercise.

This empirical effort aims to show that the changes in specialization patterns described above, and the associated gain or loss of intangible knowledge assets and expertise, are linked with innovation performances in a manner that call into question the normative emphasis behind the terms “upgrading” and “downgrading.” Specifically, **the section will show that there is little difference between entering or exiting a pre- or post- production specialization; however, there is significant difference between exit and entry when grouped as ‘change’ on the one hand, and continuity (in either form) on the other.**

In that setting, functional change is not a generic move “up” or “down” a ladder. It is a change in where an industry sits inside a sector-specific pattern of innovation, production, and value capture, and that meaning differs by Pavitt class. This is why the same movement can mean something different in SB, SS, SII, and SD sectors: **the same shift may reflect commercialization in one class, process adjustment in another, or dependence on external innovation in a third.** The right question is not whether a function is higher or lower in abstract terms, but **whether the change matches the technological logic of the sector and the wider national production ecosystem in which the industry is embedded.** The only exception to this is, naturally, production (midstream) functions, especially in cases of hyper specialization. In that case, the data does show a clear link between production (hyper) specialization and functional ‘lock’ in and innovation stagnation.

There are 80 total observations in this version of the dataset: 4 industry types x 4 periods x 5 countries. However, since we are measuring change, period 3 serves as a baseline, offering no observations (recall that FDI Markets data begins in 2003, which corresponds to period 3 in the SID database). This translates to 60 observations, 15 each for each industry type. Of these 60, there are 17 instances of change in preproduction specializations, split perfectly between 9 instances of functional exit and 8 instances of functional entry (please note, these numbers are of the individual period-to-period instances of entry and exit and have nothing to do with the numbers in table 1, which consider a longer, 3-period, time horizon). These are associated with the changes in industry propensities for innovation, by type, reported in Table 1.

Please also note that in the previous chapter, we highlighted that Germany and Holland (Spain, Italy, and France) disproportionately make up the continuity (change) group. This is only true for the approach taken in [section 4.1 and Table 1](#), wherein the long-term patterns were determined and reported). Section 4.1 also documented how Germany and Holland both witnessed a restructuring marked by reduced diversification in line with the national specialization tilt. As such, the period-to-period changes reflect a non-systematic distribution of all countries across the groups of ‘change’ and ‘continuity’. Please refer to Items 1-4 in the appendix of this chapter for the exact location of each country-industry group (60 observations) along the function-innovation data.

Table 3. Changes in All Industry Innovativeness by Exit and Entry

	General Innovation	Product Innovation	Process Innovation	Organization Innovation
Preproduction Exit	+0.84%	-1.22%	-3.32%	-0.10%
Preproduction Entry	+2.32%	+1.14%	+1.73%	-0.13%
Postproduction Exit	+7.56%	+1.65%	+0.57%	-0.44%
Postproduction Entry	+7.24%	-3.61%	-5.37%	-6.20%

As is shown above, there is no significant difference in the innovation capacity of industries that witnessed functional entry and exit. In the previous chapter, 3, the argument was cross-sectional: industries that averaged certain specializations patterns across the time-aggregated data tended to perform better in terms of their propensity for innovation, as reported by the CIS data in the SID dataset. This does not tell us anything about the ‘flows’ of innovation capacity, but rather only the ‘stocks’; recall this argument from earlier in Chapters 1 and 2. This section argues that the long term trend is one of deepening, and the industries that ended up entrenching their core specializations whilst maintaining a relatively diversified functional structure rather than oscillating or hyper specializing perform better. This calls into question certain assumptions about the impacts of specialization changes—namely, that gaining an upstream or downstream specialization is automatically good.

Consider Table 3, which reports the period-by-period changes in terms of functional entries (FSI went from below to above one) and exits (FSI went from above to below one) of all industries irrespective of Pavitt type and country. In preproduction specializations, the entry group slightly outperforms the exit group in product and process innovation capacity, however, the differences are minute. The differences in postproduction specialization are, however, substantial, but, crucially, in the opposite direction: the 5 industry groups (by Pavitt) that entered a postproduction specialization saw an average product innovation decrease of 3.61% as opposed to an increase of 1.65% in the 8 industries that exited their postproduction position.

The data in table 3 are not reported in an effort to say that despecializing from postproduction leads to higher innovativeness, but rather to point out that **specializing does not necessarily lead to higher innovativeness**, at least not immediately (within the duration of 3 years captured by each ‘period’ in the SID). As such, this calls into question the terminology ‘upgrading’ and ‘downgrading’, at least in their assumed relationship with the term innovation evident in the common conflation of the two concepts in published scholarship as reported in chapter 1 and earlier in this chapter.

Rather, the goal is to point out that, while it could very well be that upgrading and innovation are somehow related in a theoretical manner that proves empirically evident in later studies, that manner

is not likely to be linear. Within 3-year intervals (at least), it seems that innovation capacity is, on average, unaffected by functional entry and exit.

That said, **the above exercise does not account for the by-Pavitt differences discussed above. As such, the individual observations (eg. SB-DE & SD-IT) could be cancelling each other out given different baseline innovation rates and fixed industry effects.** As such, table 3 only services 1 statistically significant purpose beyond its immediate, intuitive lessons. Namely, it permits the next empirical exercise, which combines observations of functional ‘entry’ and ‘exit’ (‘continued nonspecialization and continued specialization’) into a single group called, ‘functional change’ (‘functional continuity’). We are able to do this because we know the data does not internally conflict: if anything, the instances of ‘exit’ are associated with a higher innovation rate on average than the instances of ‘entry’. The same pattern, however, does not hold for instances of continued specialization and unspecialization:

Table 4. Changes in General Innovation by Pavitt Industry and Functional Position

	Preproduction Change	Preproduction Continuity	Postproduction Change	Postproduction Continuity
SB	+6.1%	+7.2%	+14.1% (2 <i>obs</i> only)	+5.8%
SD	-2.4%	+6.7%	+6.3%	+1.3%
SS	-1.5%	+8.1%	+6%	+6.2%
SII	+3.7%	+6.1%	0 <i>obs</i>	+5.3%

The goal of the grouping in Table 3 is not to suggest that functional exit and entry are somehow similar processes with similar outcomes of value capture **or that short term change is *bad* for innovation** performance. Rather, the point is a humbler parallel: to provide new evidence that, at least within the 3 years of the change captured by each period, entering a new functional specialization in oft-perceived ‘high value functions’ does not correlate with higher innovation performance. Since the goal is not to establish a relationship but to argue for the lack thereof, the lack of correlation is sufficient to make this point. It is evidence for the nonlinearity of GVCs and for the required distinguishing between upgrading and innovation, and accuracy of tautological terminology based on a “moving up the ladder” conceptualization assumed by many GVC studies.

Table 3 shows that, between 2003 and 2016, and while accounting for sectoral-specific innovation patterns, the European industries that changed (entry and exit) their preproduction functional position (FSI change from <1 to >1 or *vice versa*) never performed better innovatively than industries that remained (un)specialized. In SB, the difference is the smallest and is in favor of continuity. In SD industries, any change in preproduction specialization is associated with a 2.4% decrease in general innovation propensity, while upstream continuity in SD is associated with a 6.7% increase in

innovation. The same large difference is reported by SS industries: -1.5% innovation rate for the change group and +6.1% for the continuity group.

Again, this is because by-period patterns are different than the longer-term patterns described in section 4.1. In the shorter-term data, we capture, for example, the long-term oscillation pattern of Spain and France as exit, entry, as well as continuity, depending on the individual period change. Oscillation is not always *entry-exit-entry* but can also be *entry-maintain-exit*, for example, meaning in the by-period analysis, ES and FR appear almost as frequently in change and continuity as DE and NL, or at least not so disproportionately as to create a significant problem of systematic endogeneity in this simple empirical exercise, which would have happened, for example if we can used this type of empirical approach with the long-term data. As such, the differences in change and continuity reported here, and consistently throughout the data are reflecting neither of industry-fixed effects, by-country differences, or systematic link between countries and functional profiles. That said, there is a link

4.4| Conclusion: Limitations of Empirical Exercise

At this point, it is important to reiterate that the purpose of this chapter **is not to show** that functional change, particularly the gaining of a previously absent specialization, is associated with lower innovation performance. Instead, it is to show that, at least **within discrete 3-year time periods, changes in the preproduction functional position of industries, while accounting for country and Pavitt differences, are, regardless of the direction of that change, associated with lower innovation performances** as compared to industries which maintained their functional structure. While functional entry (what is more commonly known as upgrading) outperforms functional exit slightly, it does not outperform instances of continuity, both in terms of continued specialization and the more surprising, continued nonspecialization. As such, as can say that functional deepening outperforms functional entry, again calling into question the notion of ‘upgrading’, which largely ignores the issue of deepening.

The empirical evidence presented in this chapter compels a critical re-evaluation of the linear, normative assumptions embedded within much of the Global Value Chain (GVC) upgrading literature. Far from a universal escalator to enhanced innovation, our findings suggest that functional entry into ostensibly “higher-value” activities does not automatically translate into superior innovation performance. Instead, the data reveal a nuanced reality where functional continuity—the sustained specialization and deepening of capabilities within existing pre- or post-production functions—often correlates with more robust and consistent innovation rates, at least in the short (immediate) term. For instance, the consistent and deepening specialization of German Science-Based (SB) industries in post-production functions, as detailed in Section 4.2, demonstrates a clear link to sustained innovation capacity, contrasting sharply with the more volatile innovation propensities observed in industries undergoing frequent functional shifts. This introduces the concept of a “stability premium” in innovation, where the benefits of accumulated tacit knowledge, established routines, and stable inter-firm relationships within a specific functional domain outweigh the disruptive costs associated with frequent structural shifts. This challenges the implicit “moving up the ladder” narrative, arguing instead for a more dynamic, path-dependent understanding of innovation within GVCs, where strategic deepening can be as, if not more, impactful than upgrading.

The observed “stability premium” carries significant implications for industrial policy, particularly within advanced economies like those in the European Union. Current policy frameworks often implicitly or explicitly incentivize industries to undertake functional entry into perceived high-value activities, frequently through subsidies for R&D or advanced manufacturing. However, our results indicate that such policies, while well-intentioned, may inadvertently disrupt established innovation ecosystems without guaranteeing commensurate returns. Instead, policymakers should pivot towards strategies that foster functional deepening. This involves supporting long-term investments in specialized human capital, advanced infrastructure, and collaborative networks that reinforce existing functional strengths. A prime example is the German automotive industry, which, beyond traditional manufacturing, has increasingly focused on deepening its expertise in digital services, software development, and advanced logistics. This strategic deepening, perhaps supported by targeted vocational training and research initiatives, allows for continuous innovation within established areas of competitive advantage.

The patterns of “functional oscillation” observed across several European industries—characterized by frequent entries and exits from pre-production specializations without sustained innovation gains—raise critical questions about Europe's competitive positioning in global value chains. While

countries like Germany demonstrate a capacity for sustained functional deepening, particularly in post-production, the broader European landscape suggests a struggle to consistently anchor high-value activities. In an era defined by intense technological competition and strategic industrial policies from global players like the United States and China, such oscillation represents a vulnerability. For instance, the US CHIPS and Science Act aims to reshore and deepen semiconductor manufacturing and R&D capabilities, while China's "Made in China 2025" initiative strategically targets leadership in advanced manufacturing and high-tech sectors, consolidating control over critical upstream (R&D, design) and downstream (branding, data analytics) functions. Mediterranean Europe's inability to consistently deepen its functional specializations risks relegating its industries to a perpetual state of catching up, rather than leading, in the global innovation race, as highlighted by concerns over Europe's declining competitiveness in GVCs. This underscores the urgency for a coherent, long-term European industrial strategy that prioritizes stability and cumulative learning over transient positional shifts.

The analysis here suffers from some limitations that merit a dedicated discussion. First is the lack of observations by industry type in postproduction functional change, especially, functional entry. This does impede the ability to make the primary argument that innovation performance is not positively linked to functional change, regardless of the direction of that change. It also impedes the ability to derive conclusions about the differences in behavior between industry types, where 2 out of 4 of the industries discussed lacked postproduction entry observations.

Despite this, it is important to note that while this version of the data only includes 60 analytical observations, **each observation represents hundreds of inward FDI projects and thousands of firm-level questionnaires aggregated at the highest possible level** (4 industry types and 3 functional groupings), as such, drowning out a great deal of 'noise' and presenting a massive—albeit condensed—amount of data.

A second shortcoming that could be addressed in future iterations of this work has to do with the SID data structure. The SID data is based on CIS waves, which, in this case, is not ideal for contextualizing business cycles within the context of economic crises, particularly the 2008 Financial Collapse. Future studies should ground this discussion in the notion of 'ability to withstand economic crises'. As suggested by Coveri and Zanfei, diversified industries are more capable of resisting pressure from external crises due to their versatility of specializations, allowing for quicker recombination of functions to respond to changes in market structure and institutional change. An ideal time-period structure for studying this would combine years purposefully to reflect a baseline before the crisis, a second period reflecting the crisis years, and a third period reflecting post crisis. Due to the structure of the CIS-based SID, however, that is not possible. Also, the fact that the data ends in 2016 prevents examinations of more modern business cycles and structural change, as well as the Covid Pandemic and ensuing economic crisis.

Finally, a third shortcoming has to do with the scope of this discussion, which seeks to provide evidence for the weakness of the term 'upgrading' with its inherent linearity and assumed favorable outcome of functional entry. As such, evidence did not consider overall functional profiles such as in the second half of the previous chapter. In other words, future works should consider the difference in innovation performance given simultaneous change in pre- and post- production functions such as the cases highlighted at the beginning of section 4.2.

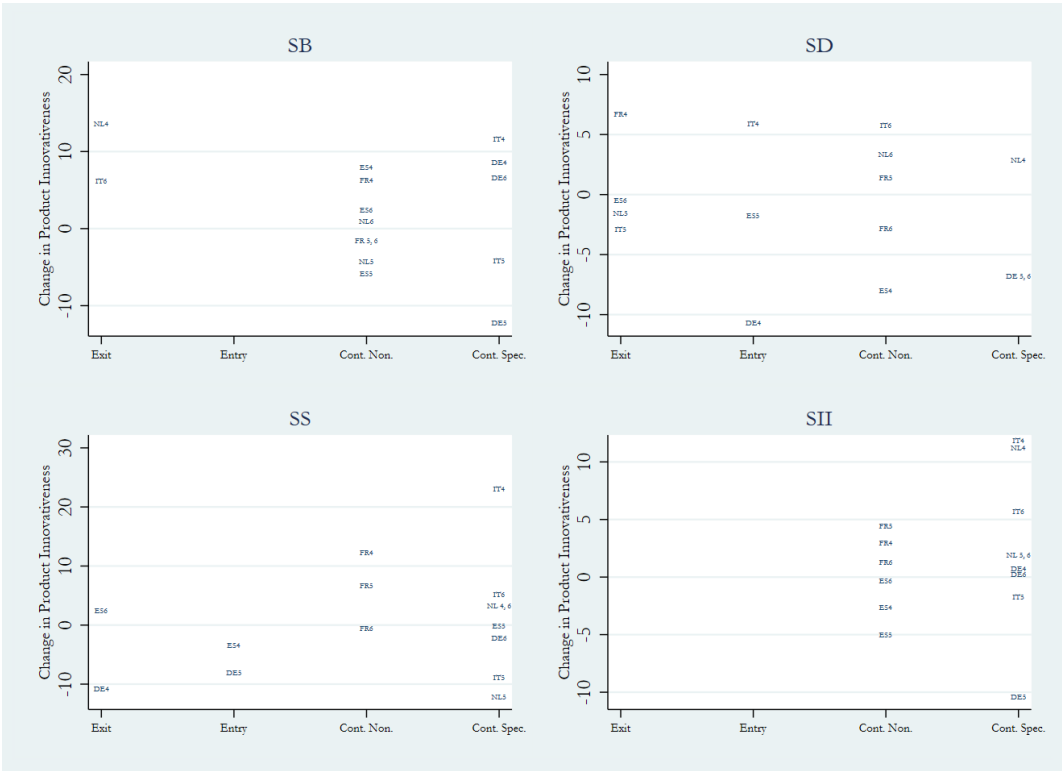
Chapter 4 References

- Boschma, R., Hernández-Rodríguez, E., Morrison, A. & Ye, X. (2025a). Functional Upgrading and Downgrading in Global Value Chains: Evidence from EU Regions Using a Relatedness/Complexity Framework. *Papers in Regional Science*, 104, 1-16. <https://doi.org/10.1016/j.pirs.2024.100072>
- Boschma, R., Hernández-Rodríguez, E., Morrison, A., & Pietrobelli, C. (2025b). Do global value chains and local capabilities matter for economic complexity in EU regions? UNU-MERIT. UNU-MERIT Working Papers No. 002 <https://doi.org/10.53330/BAGR7168>
- Bogliacino, F. & Pianta, M. (2016). The Pavitt Taxonomy, Revisited: Patterns of Innovation in Manufacturing and Services. *Economia Politica*, 33(2), 153-180
- Blazek, J. (2015). Towards a Typology of Repositioning Strategies of GVC/GPN Suppliers: the Case of Functional Upgrading and Downgrading. *Journal of Economic Geography*, 849-869. doi:10.1093/jeg/lbv044
- De Marchi, V., Di Maria, E., Gulini, R., & Perri, A. (2020). Nurturing International Business research through Global Value Chains literature: A Review and Discussion of Future Research Opportunities. *International Business Review*, 29(5), 1-16. <https://doi.org/10.1016/j.ibusrev.2020.101708>
- Dosi, G., Faillo, M. & Marengo, L. (2008). Organizational Capabilities, Patterns of knowledge Accumulation and Governance Structures in Business Firms: an Introduction. *Organization studies*, 29(8-9), 1165-1185
- Fuchs, E. & Kirchain, R. (2010). Design for Location? The Impact of Manufacturing Offshore on Technology Competitiveness in the Optoelectronics Industry. *Management Science*, 56(12), 2323-2349
- Kordalska, A. & Olczyk, M. (2023). Upgrading Low Value Added Activities in Global Value Chains: a Functional Specialisation Approach. *Economic Systems Research*, 35(2), 265-291, DOI: 10.1080/09535314.2022.2047011
- Morrison, A., Pietrobelli, C., & Rabellotti, R. (2008). Global Value Chains and Technological Capabilities: A Framework to Study Industrial Innovation in Developing Countries. *Oxford Development Studies*, 36(1), 39-58. <http://dx.doi.org/10.1080/13600810701848144>
- Pavitt, K. (1984). Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory. *Research policy*, 13(6), 343-373
- Pietrobelli, C. & Rabellotti, R. (2011). Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? *World Development*, 39(7), 1261-1269. doi:10.1016/j.worlddev.2010.05.013
- Pisano, G. & Shih, W. (2009). Restoring American Competitiveness. *Harvard business review*, 87(7/8), 114-125
- Van Assche, A. (2017). Chapter 45: Global Value Chains and Innovation. In Bathelt, H., Cohendet, P., Henn, S., & Simon, L. The Elgar Companion to Innovation & Knowledge Creation (Pp. 739-751). Edward Elgar publishing Cheltenham, UK • Northampton, MA, USA DOI 10.4337/9781782548522

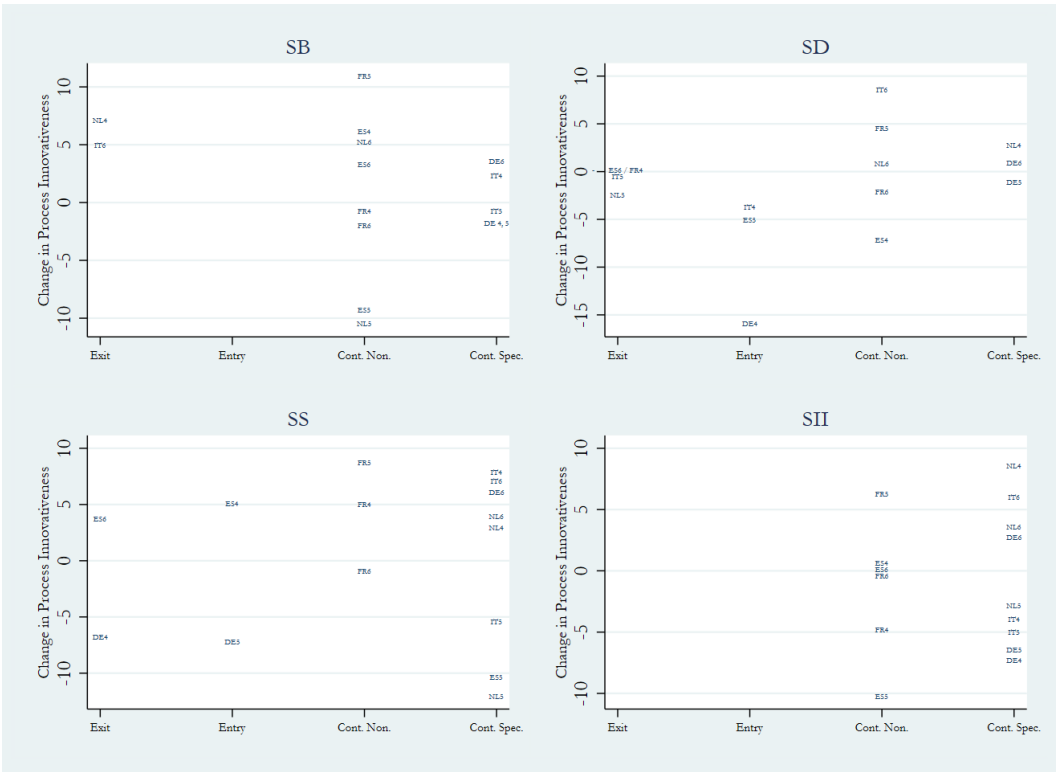
Item A. Changes in Product Innovativeness and Upstream Specialization by Pavitt



Item C. Changes in Product Innovativeness and Downstream Specialization by Pavitt



Item D. Changes in Process Innovativeness and Downstream Specialization by Pavitt



Chapter 5 | Conclusions and Policy Recommendations

5.1 | Overview and Summary of Findings

This dissertation has examined, both conceptually and empirically, the relationship between functional specialization and innovation performance within European industries embedded in global value chains (GVCs). Drawing upon the Sectoral Innovation Database (SID) and FDI Markets (FDI-M), the research contributes original quantitative evidence on 38 manufacturing and service industries across five advanced European economies—Germany, France, Italy, Spain, and the Netherlands—together accounting for approximately 70% of the European Union’s GDP. In doing so, this work extends the “smile-curve” hypothesis that upstream and downstream specializations command higher value capture than midstream specializations beyond its traditional interpretation in terms of monetary value capture to encompass innovation outcomes as a distinct and measurable dimension of value creation.

5.1.1 | Reframing the Study of Innovation in GVCs

Chapter 1 argued that a persistent weakness in the GVC literature is a shared problem in the wider innovation literature: the inadequate conceptualization and empirical measurement of innovation. Much of the existing scholarship has treated innovation as either *exogenous* to economic performance—conflating it with generic “technology” variables—or *endogenous but unobserved*, inferred from favorable positional changes within value chains, thereby unintentionally routinely equating it with the notion of *upgrading* (Pietrobelli & Rabellotti, 2011). Against this backdrop, a more direct approach is proposed, adopting a definition of innovation based on the endogenous capacities of firms as reflected in repeated routines and behavior outside the of GVCs and based on industry data sourced from the firm level, and measures that go beyond R&D expenditures or patent data.

Rather than viewing competition and specialization in terms of final products or sectors, our approach throughout this dissertation conceptualizes the economy as a network of functions—preproduction (e.g. R&D, design), production (eg. manufacturing and construction), and postproduction (e.g. marketing, logistics, after-sales services)—whose relative composition in terms of Intangible Knowledge Assets (IKAs), in part, determines an industry’s innovation potential. This conceptualization was necessary to capture the rising centrality of (IKAs)—design capabilities, data, organizational routines, and relational capital—which increasingly underpin competitive advantage in GVCs (Corrado et al., 2005; 2006); and it forms part of a growing segment in GVC literature adopting a non-normative, two-way conceptualization of ‘upgrading’ in which firms may experience both upgrading and downgrading without either necessarily being ‘good’ or ‘bad’ (Blazek, 2016).

By repositioning the analytical lens in this way, Chapter 1 provided the theoretical foundation for the empirical work that followed. It showed that innovation must be examined not merely as a by-product of technological accumulation but as an organizing principle of global production, directly shaping where and how value is created, captured, and redistributed.

5.1.2| Data and Empirical Operationalization

Chapter 2 translated these conceptual propositions into a measurable empirical strategy through the integration of two databases: (1) FDI Markets (FDI-M) and (2) the Sectoral Innovation Database (SID):

(1) *FDI Markets* records greenfield investment projects, thus capturing the “equity participation of multinational corporations (MNCs) in the locations where they operate” (Coveri et al., 2024: 6). Although inward greenfield FDI is only one sub-type of GVC linkage, it constitutes a revealing proxy for functional positioning in GVCs, since the comparative distribution of FDI projects closely mirrors the relative allocation of technologically embodied and knowledge-intensive tasks across borders. In other words, it reflects the “actual involvement” of industries in GVCs (ibid)—i.e. it is a specialization index based on, but that extends beyond, greenfield FDI and a sub-type of GVC (hierarchical) to reflect the available technologies and factor endowments of industries. Hence, while the FSI does not exhaust all GVC forms, it offers a consistent empirical handle on functional specialization. Thus, we compute the relative Functional Specialization Index (FSI) based on Balassa’s (1965) concept of revealed comparative advantage.

Combining this FSI indicator with SID—a comprehensive industry-level repository of innovation indicators—enabled the construction of a merged dataset (referred to as SID-FDI or FDI-SID throughout this research) capable of studying the connection between functional positioning and capacity for innovation in a manner consistent with chapter 1’s findings. Chapter 2 presented extensive descriptive statistics, several of which warrant reiteration here because of their interpretive importance:

- **Sustained growth of inward FDI:** excluding the crisis years surrounding the 2008 financial collapse, each year from 2003 to 2016 recorded an increase in total inward FDI.
- **Volume and distribution:** the five economies together received 16,084 FDI projects (10,000 projects are excluded due to being incompatible with SID structure). Germany absorbed 42 %, France 24 %, Spain 17 %, the Netherlands 10 %, and Italy 7 %.
- **Functional pattern:** all functions registered growth, except for production functions, lagged markedly behind. There is no surprise here as the population of countries present in the data are the 5 largest EU economies, which do not specialize, on a global scale, in production.
- **Functional hierarchy:** the largest inflows were observed in sales, marketing, and support (6,198 projects), manufacturing (2,725), business services (2,485), logistics and distribution (1,399), and headquarters (1,078). The smallest inflows were in extraction (7 projects, confined to chemical industries), electricity (9), shared services (35), recycling (41), and customer contact centers (56).
- **Industry distribution:** publishing attracted the highest number of FDI (2,274), followed by computer and electronic manufacturing (1,625), machinery and equipment manufacturing (1,196), computer programming and information services (883), and legal, accounting, and consultancy services (868). On the opposite extreme, trade and repair of vehicles (5), printing

of recorded media (26), courier activities (42), wholesale trade (55), and water transport (79) registered minimal inflows.

- **Temporal concentration of innovation:** innovation activities, broadly defined, have become more concentrated over time with earlier periods (1994–2000) showing dispersed patterns, and later periods (2012–2016) exhibiting convergence.
- **Cross-national comparison:** Germany emerged as the most consistently innovative economy, with very few industries reporting less than half of firms introducing innovations on average. Italy and Spain showed the lowest propensities for innovation, generally, while France and the Netherlands occupied intermediate positions.
- **Sectoral profiles:** science-based (SB) industries displayed the highest overall innovation propensities, supplier-dominated (SD) industries the lowest. Scale and information intensive (SII) and specialized-supplier (SS) industries showed comparable levels, except in process innovation, where Europe’s relative nonspecialization in production stages yields systematically lower rates.

Together, these patterns reveal a Europe where innovation is functionally uneven and increasingly intangible-intensive. The descriptive analysis laid the groundwork for a more formal statistical exploration of how such functional structures relate to innovation outcomes.

5.1.3 The Specialization–Innovation Nexus

Chapter 3 continued the analysis by formalizing the specialization–innovation nexus. It located the relationship between specialization and innovation within the broader acceleration of intangible intensity in GVCs. As global production has shifted from tangible manufacturing to knowledge-rich activities, the distribution of gains from trade has likewise shifted. The analytical unit of interest is therefore no longer the *product* but the *function* through which value and innovation are generated.

Within this framework, functional specialization emerges as a decisive determinant of innovation performance. Yet most prior empirical work has focused exclusively on monetary value capture, measuring value in terms of revenues, profits, or gross value added. The present research extends this logic to innovation capacities, proposing that innovation capacity acts as an intermediate mechanism linking intangible assets with value capture. The limitations of this approach are discussed in section 5.3.

Drawing on the merged SID–FDI dataset, the analysis covered 38 industries across the five economies between 2003 and 2016. Quantitative models yielded several key results:

1. **Extension of the Smile-Curve Hypothesis:** industries specialized in *pre-* and *post-production* functions exhibit significantly higher innovation rates than those specialized in production. This pattern demonstrates that the “smile curve,” originally conceived in terms of value added, also holds for innovation performance.
2. **Functional Diversification and Innovation:** across all sectors, higher *functional diversity*—the dispersion of specializations across multiple individual GVC functions—is associated with stronger innovation outcomes, particularly in product innovation. This relationship remains

robust even after accounting for industry size, total FDI inflows, industry innovation expenditures, and country fixed effects in a controlled econometric investigation ([section 3.4](#)).

3. **Sectoral Asymmetry:** the diversification effect is statistically and substantively significant only in service industries, not in manufacturing. In Manufacturing, innovation correlates primarily with the *volume* of FDI projects, regardless of their *functional distribution*. In Services, by contrast, the pattern of FDI distribution—the relative mix and distribution of activities in all streams of production—matters greatly.

Statistical analyses confirmed these findings, leading to the acceptance of the following hypotheses:

- **HA1:** specialization in pre- and post-production functions is associated with higher innovation rates than specialization in production.
- **HC1:** more functionally diversified industries exhibit higher innovation rates.

5.1.4 Deepening – v – Upgrading

Chapter 4 argues that the relationship between upgrading and innovation is far more conditional than a simple “move up the ladder.” Using the time dimension in the merged SID–FDI dataset, the chapter shows that functional entry into a higher value (upstream or downstream) position is not automatically innovation-enhancing; in many cases, it is associated with weaker short-run innovation propensities. The central interpretive point is that what looks like upward movement can instead be a disruptive transition that temporarily lowers innovation capacity, whereas sustained specialization inside an existing functional profile often supports more stable innovation performance.

The chapter’s deeper contribution is therefore to recast GVC positional change as a tension between change and continuity, not a linear ascent, directly linking it to the evolutionary economic discussion of routines, heuristics, and firm capabilities. Across the European cases, the evidence points to a clear stability premium, especially where industries deepen entrenched postproduction or preproduction specializations rather than oscillating between functions. This is most visible when this entrenchment is in line the national specialization pattern: Germany increasingly deepens downstream and market-interface functions, while the Netherlands consolidates upstream HQ-oriented specialization, and Spain and France show more factory-like entrenchment in production. The broader implication is that functional upgrading is not a universal good; its effects depend on whether it builds cumulative capabilities or merely shifts firms into new roles without the learning base needed to sustain the positional with what that entails in terms of developing, deploying, and adapting to changes IKAs.

5.2| Theoretical and Empirical Contributions

The results presented in this work make a series of substantive contributions to both the theory and empirical analysis of innovation in global value chains (GVCs). Collectively, they position this dissertation at the intersection of Economics, Evolutionary Economic Geography, innovation studies, and International Business (IB). In doing so, the research advances a conceptualization of innovation dynamics that centers on functions, not products, as the fundamental analytical unit of competitiveness in an economy increasingly shaped by IKAs.

5.2.1| From Product- to Function- Based Frameworks

A central theoretical move in this dissertation is the classification of the analytical focus from product-based to function-based competition. Traditional GVC frameworks, emerging from the global commodity-chain tradition (Gereffi, 1994; Humphrey & Schmitz, 2002), typically view GVCs in terms geographically dispersed regions specializing in products and intermediate products along the value chain. **This view has served policy debates well** but fails to explain how, within a single sector, firms and regions can occupy vastly different positions along the value chain and experience correspondingly divergent innovation outcomes.

By contrast, the increasingly adopted function-based approach recognizes that innovation is not the property of the product but of the activity. This shift in the analytical lens enables a more granular understanding of the geography of innovation. It reveals that preproduction functions such as training and design, and postproduction functions such as marketing and logistics, boast a disproportionate share of innovative effort and capacity as compared with production functions such as construction or extraction. This is the empirical essence of the innovation-extended smile curve discussed in Chapter 3.

The argument builds upon and extends the insights of Cohendet and Simon's (2017) open and interactive model of innovation, which conceives of innovation as a 'capacity' for novelty gained through interactions with multiple knowledge communities. Within GVCs, these communities are often functionally differentiated, thus representing the multiplicity of knowledge assets. By operationalizing this idea through the FSI, the dissertation provides a measurable representation of how functional distribution shapes innovation capacities.

5.2.2| Intangible Knowledge Assets as Changing the Role of Innovation in GVCs

The second theoretical contribution concerns the centrality of intangible assets as the structural underpinning of innovation within GVCs. The global economy has witnessed a profound shift from tangible capital accumulation—machines, buildings, and inventories—to intangible asset formation, encompassing software, research, design, data, brand equity, and organizational competencies (Corrado et al., 2005; Timmer et al., 2019). These assets are inherently non-rival and often exhibit strong spillovers, meaning that their productivity increases with diversity and interaction rather than with scale alone.

The empirical findings confirm that industries specialized in intangible-intensive functions exhibit superior innovation outcomes than those specialized in tangible-intensive functions. **While existing studies have described intangible assets as determinants of profitability or productivity, few**

have demonstrated their specific role as mediators between functional specialization and innovation performance. This dissertation therefore contributes to closing the conceptual gap between the literature on intangible assets and that on GVC functional positioning by examining the role of innovation capacity as the crucial pathway through which GVC positional change is sustained and utilized for economic profit.

Furthermore, by revealing that functional diversity matters only for service industries, the study provides an explanation for the long-observed heterogeneity between manufacturing and service innovation systems. In the service sector—particularly in the KIBS—intangible assets are not only inputs to innovation but also the medium through which innovation occurs. The collaborative, project-based nature of KIBS means that functional diversification generates new knowledge. Manufacturing, by contrast, remains more path-dependent: innovation tends to be capital-intensive and incremental, less sensitive to functional diversity.

This distinction refines existing taxonomies of innovation regimes, extending Pavitt's (1984) and Pianta's and Bogliacino's (2016) classification by introducing the concept of functional configuration—the specific mix of functions in which an industry is specialized—as a determinant of its innovation dynamics. It also links to the evolutionary perspective in which the accumulation and recombination of capabilities are central mechanisms of economic change (Nelson & Winter, 1982).

5.2.3 | Dual Nature of the Smile Curve

Another contribution concerns the empirical extension of the well-established specialization–value nexus to the innovation propensities of industries. In GVC theory, functional specialization has long been associated with patterns of value capture: pre- and post-production activities generate higher value than production functions. This dissertation demonstrates that the same rule holds for innovation rates—industries specialized in upstream and downstream functions are not only more profitable but also more innovative.

The implication is profound: innovation is not merely a driver of value capture but itself structured by the fragmentation of global production. The “smile curve” hypothesis thus possesses a dual dimension, economic and innovative, each reinforcing the other. Moving toward pre- and post-production functions does not only improve margins; it also enhances the system's capacity for self-renewal through innovation. This insight resonates with the growing policy emphasis on innovation-driven re-industrialization in Europe.

5.2.4 | Data Integration and Measurement Innovation

The dissertation makes several methodological advances that are themselves valuable for future research. First, the merger of SID and FDI-M data provides a unique cross-country, cross-industry panel capturing both innovation performance and functional specialization.

Moreover, the successful use of the Functional Specialization Index (FSI) modeled after Balassa's (1965) revealed comparative advantage and of greenfield *FDIs* as a proxy for functional positioning confirms the methodological relevance of these novel indicators developed by Antonello Zanfei and Andrea Coveri. This measure captures a large portion of underlying comparative advantage as defined by technologies and factor endowments. When applied correctly, the FSI shows how countries transition across functional groups and how these shifts correspond to changes in innovation

performance. Although FDIs reflect only a subset of GVC relationships, they signal strategic commitments of multinational firms and thereby capture differences in the geography of functions. By combining these data with innovation indicators, the dissertation generates a nuanced empirical picture of Europe's functional innovation landscape between 2003 and 2016.

5.2.5 | Conceptual Refinements, Emerging Hypotheses, and Scholarly Implications

The analysis of diversification effects implies that it is not only the presence of multiple functions but their specific combinations that matter for innovation. For instance, the co-location of R&D with marketing may foster rapid feedback loops between technological and market knowledge, whereas pairing logistics with design might yield limited returns. This suggests a future research agenda focused on identifying synergistic functional constellations within industries.

Taken together, these contributions redefine the way scholars might approach innovation in an era of intangible globalization. They suggest that:

1. Innovation capacities cannot be detached from the functional architecture of global production and innovation networks.
2. Functional specialization provides a more accurate lens than product specialization for analyzing innovation capacities consistent with the dedicated literature on the topic.
3. Functional diversity constitutes a potent engine of innovation, particularly in service-oriented economies.
4. Empirical analyses must source their theories using an integrated, cross-disciplinary approach that captures both economic structure and knowledge dynamics.

These insights align with the evolving research agenda on global innovation networks (GINs) (Ernst, 2009; De Marchi & Giuliani, 2017) and offer a robust empirical framework for examining how innovation capacity is embedded within functional and spatial structures.

5.2.6 | Global Implications (Beyond Europe)

Global Value Chains are a universal phenomenon. Dramatically few, if any, countries entirely avoid participating in GVCs. Given the increasing specialization of countries along the lines of function, the results presented in this dissertation have implications beyond the European context. While the generalizability of this study because of its limited geographic scope is considered a limitation (see [section 5.3.2](#)), it is also at once a strength that allows us to make certain claims about the sources of innovation heterogeneity in highly advanced economies using the GVC framework.

Typically, comparisons in the GVC framework contrast advanced and emerging economies. The functional insight that emerges from this is similar to that advanced in Chapter 3: intangible-intensive specializations are often linked with higher value capture than their tangible counterparts. As mentioned in the preceding chapter, however, the comparison between functions of the same 'value' is often overlooked. As such, less is known about the source of innovation heterogeneity in advanced economy firms occupying different but similarly good functional positions along Value Chains.

This dissertation makes several contributions in that area, prime amongst which is the *smile tilt* hypothesis advanced and discussed in Chapters 3 and 4: industries that *deepen* specializations in the

direction of the national Functional Specialization Profile (FSP) (whatever it may be) without sacrificing functional diversity are expected to reap larger innovation capacity gains than industries that deepen an equally ‘valuable’ functional position *away from* the national FSP tilt (this hypothesis is put forward particularly owing to the data concerning Germany and the Netherlands).

This hypothesis and the underlying logic of Chapter 4 allows for more meaningful comparisons between advanced economies. This is an area where the heterogeneity in firm innovation capacities is not so streamlined and well-understood in the literature. Moreover, given Europe’s so-called “innovation-deficit” problem, hypotheses and theories concerned with explaining this heterogeneity relative to the USA and China (Europe’s main comparators).

5.3 | Limitations and Implications for Future Research

The empirical strategy and analytical framework developed in this dissertation inevitably entail limitations that constrain the accuracy and generalizability of the findings and delineate fertile ground for future research. A careful reflection on these limitations is not merely an exercise in caution; it is an integral part of consolidating the scientific contribution and charting the agenda forward.

5.3.1 | Measurement and Data Construction

A first set of limitations arises from the choice of measurement, particularly the reliance on inward FDI, by number, as a proxy for functional specialization. While this offers several advantages—most notably in terms of parsimony—it also introduces interpretive caveats that merit explicit discussion:

The principal issue concerns the absence of monetary valuation in the calculation of the Functional Specialization Index (FSI). In this dissertation, functional specialization was measured in terms of *number of projects*, rather than the *monetary value* of investment. This choice, grounded in parsimony and comparability, ensured that the analysis could treat all functions symmetrically. However, it also obscures heterogeneity, in fact an inverse correlation, in project size and capital intensity across functions. The main issue here concerns the functions at either end of the smile curve: preproduction functions typically involve larger-scale and higher-value investments per project than postproduction functions.

Consequently, an identical increase of, for example, 10 FDIs in R&D versus 10 in sales does not carry the same economic weight. The omission of monetary values may therefore understate the significance of high-value, low-frequency functions and overstate the role of low-value, high-frequency ones. Thus, cross-industry comparisons based purely on counts must in the future be re-examined in terms of the investment capital behind the number of projects in each functional group.

Relatedly, the FSI based on FDI data captures a specific type of global value chain participation, namely those governed through hierarchical, equity-based relationships—in other words, GVCs in which multinational corporations exert direct ownership and control through foreign affiliates. This corresponds to Gereffi et al.’s (2005) classification of hierarchical, quasi hierarchical, and, to a lesser extent, captive governance. However, as authors reviewed in this dissertation emphasize, a growing share of global value creation now occurs through networked or relational GVCs, including inter-firm collaborations and open innovation ecosystems. These *networked* relationships are less likely to be captured in FDI data, which means that the empirical window offered here, while significant, is partial.

Nevertheless, as argued in the text and as is consistent with Coveri et al. (2024), the correlation between FDI patterns and comparative advantages based on factor endowments suggests that the FSI “largely reflects the actual involvement of regions in GVC stages” (Coveri et al., 2024: 6). In other words, although the indicator captures only one subset of GVCs directly, it indirectly approximates the structural specialization patterns of the industry in other GVCs structures.

5.3.2| Geographic, Temporal, and Sectoral Scope

The analysis focused on five major European economies—Germany, France, Italy, Spain, and the Netherlands—representing roughly 70% of EU GDP. While this coverage provides a solid empirical foundation for the purposes of our research, it necessarily omits smaller and peripheral economies, particularly those in Central and Eastern Europe (CEE), whose functional position might be closer linked to production activities. Additionally, including these economies in future analyses could reveal variations in how functional specialization and innovation capacity interact under different institutional and developmental conditions. As it stands, our results are only generalizable to advanced economies, and ones with extremely similar geographical and institutional ties, such as the EU-5 present in this study.

The temporal coverage of 1994–2016 also imposes limits. Although this period spans two decades of substantial transformation, it ends just before major events such as the COVID-19 pandemic and the green transition acceleration. Perhaps most importantly for the results concerning the link between diversification and innovation, the time span keeps out the crucial transformation concerning the digital platformization of manufacturing. Recalling from chapter 1 the link between technology and innovation, extending the analysis to more recent years would make it possible to assess whether the patterns identified have intensified or evolved under these new technological conditions. Given the timespan of both the SID and FDI-M, this was not possible in this work. Future studies should seek to extend datasets such as these and replicate the findings between 2016 and 2025.

A related limitation concerns the service–manufacturing dichotomy. The empirical finding that functional diversity drives innovation in services but not in manufacturing raises questions about the generalizability of this relationship across different industrial contexts. Manufacturing sectors may still benefit from functional diversity, but through different mechanisms such as vertical integration of design and production or embedded supplier networks. Future studies could disaggregate Manufacturing into subcategories (e.g. high-tech vs. low-tech manufacturing) to examine whether the observed asymmetry persists or varies with technological intensity.

Similarly, future studies could further disaggregate Services into KIBS and non-KIBS. This follows from the works of CHS covered in this research, which suggest, and directly contribute to, creating the EU Klems dataset, which explicitly argues that the source of IKAs is the KIBS industries. Since this dissertation never isolated and examined the KIBS industries on their own, future studies could seek to do that by identifying convergences and divergences in innovation patterns and functional specialization/diversification with the following 5 industries grouped as the KIBS ‘sector’:

J62: computer programming, consultancy, and related activities

J63: information service activities

M72: Scientific research and development

M73: Advertising and market research

N: Administrative and support service activities

5.3.3| Analytical and Theoretical Boundaries

At the analytical level, several theoretical simplifications warrant recognition. the models constructed in chapter 3: section 4 inherently assume that specialization and innovation are linearly related, yet in

reality, their relationship may be non-linear and contingent. Similarly, while the regression models control for country and industry fixed effects, unobserved institutional variables, most importantly the regulatory environments and labor market institutions, may condition the specialization–innovation relationship in ways not captured here. Despite all being EU, the 5 countries in our dataset do display differences particularly across those two would-be variables.

Moreover, our empirical models (only in the regression analysis) treat innovation performance as a dependent outcome rather than as a co-evolving process. In practice, innovation is both shaped and is shaped by functional specialization. Firms that innovate may reconfigure their functional position in GVCs by, say, internalizing R&D or outsourcing production, based on the kinds of innovation that are feasible. Capturing this co-evolution would require dynamic modelling approaches or longitudinal case studies that trace causal sequences over time.

Another analytical limitation lies in the treatment of GVC integration. While the dissertation tested whether the specialization–innovation relationship intensifies with deeper GVC participation (HB₁), the proxy used—volume of inward FDI—may not fully capture the multi-dimensional nature of integration. Integration involves more than just investment *volumes*. Future research could incorporate alternative measures, such as trade-in-value-added (TiVA) indicators, participation in cross-border R&D collaborations, or data on inter-firm knowledge exchange networks, to provide a richer picture of how integration mediates innovation outcomes.

5.3.4 | Methodological Implications for Future Research

The limitations discussed above open several promising directions for future inquiry. First, future studies could revisit the analysis using monetary values of FDI to verify whether the patterns observed in terms of counts hold when weighted by investment scale. This could provide a more (or perhaps less—but surely differently) accurate assessment of the economic significance of each function and allow a closer examination of the relationship between innovation capacity and capital deepening.

Second, researchers could integrate firm-level microdata to complement the industry-level data used here. Data used in this study is industry data, despite being sourced from questionnaires with manager-respondents. Microdata would permit the analysis of heterogeneity within industries and reveal whether the specialization–innovation nexus operates similarly for small and large firms, domestic and foreign-owned firms, or firms embedded in different governance structures.

Third, future work could adopt mixed-method or multi-level designs combining quantitative analysis with qualitative case studies. For instance, in-depth sectoral studies could trace how firms organize their functions across countries and how this influences innovation routines. Comparative cases between, say, German automotive firms and Dutch digital services firms could illuminate how institutional and organizational factors mediate functional specialization within equally intangible functional positions.

Fourth, there is scope for cross-regional comparison beyond Europe. Applying the same analytical framework to Asian or North American economies could test whether the specialization–innovation relationship holds under different developmental models and institutional architectures, as mentioned prior in reference to the CEE countries. This would also facilitate comparative policy learning:

Europe's strength in services and intangible assets could be contrasted with Asia's manufacturing-led innovation strategies.

Finally, as new data emerge—such as the *OECD* Analytical Business Enterprise Research and Development ([ANBERD](#)) database, Eurostat's Structural Business Statistics ([SBS](#)), and Horizon Europe project databases, including [EU Klems](#) and [GLOBALINTO](#)—researchers will have the opportunity to construct more indicators of functional participation and innovation, including discriminating between and knowledge stocks and flows, where the latter is a better proxy of the effect of GVC participation on learning. The integration of these datasets with SID and FDI-M would enable mapping of Europe's evolving innovation landscape across both tangible and intangible domains.

5.4 | Policy Recommendations

The findings presented throughout this dissertation—particularly the confirmation that functional specialization and functional diversity jointly shape innovation outcomes—carry important implications for the design of innovation, industrial, and regional policies within the European Union. At a time when global value chains are being reconfigured by technological disruption, geopolitical realignment, and environmental imperatives, the evidence provided here calls for a rethinking of where and how policy seeks to foster innovation capacity.

5.4.1 | Translating the Specialization–Innovation Nexus into Policy Action

From a policy standpoint, our findings imply that European innovation policy must move beyond product-based and sectoral approaches and adopt function-based and capability-oriented strategies. These would recognize that economic value and innovation potential increasingly accrue to functions such as design, R&D, marketing, data analytics, and customer experience management—the same functions where Europe already possesses comparative advantages in many regions.

The concept of functional specialization thus provides a lens for operationalizing long-standing EU objectives: competitiveness, cohesion, and technological sovereignty. The empirical confirmation of the innovation-extended “smile curve” in this dissertation suggests that policy should actively support the pre- and post-production while enabling firms and regions to combine functions across boundaries. That said, the suggestion by the discussion that combinations matter does warrant caution in crafting policy based solely on the above.

At the heart of the specialization–innovation nexus lies the growing importance of intangible assets, including organizational routines, software, design capabilities, and brand equity. These are the assets that enable firms and regions to generate and absorb knowledge, collaborate across networks, and participate meaningfully in GVCs. Policy should therefore prioritize the accumulation and diffusion of intangible knowledge assets through several avenues:

1. Investment in Skills (Human Capital):

Intangible functions, which are most strongly associated with innovation, are also those most dependent on highly skilled labor and creative competencies. European initiatives such as the [European Skills Agenda](#), the [Digital Education Action Plan](#), and the [Pact for Skills](#) should ensure that skills development anticipates the evolving functional composition of industries. Regions specializing in postproduction functions, for example, may require targeted support for marketing analytics, digital content creation, or data-driven customer engagement skills. However, as the most important finding of this dissertation suggests, deepening must be balanced with asset multiplicity.

2. Support for ‘Non-Bankable’ Innovations:

Innovation policy has traditionally privileged technological breakthroughs, yet this study demonstrates that much of the innovative activity occurs in services and knowledge-intensive business sectors (KIBS). EU innovation frameworks such as the [European Innovation Council \(EIC\)](#) should continue to broaden eligibility criteria to explicitly include non-technological innovation and cross-functional integration projects, which has been a weakness of such institutions in the past.

3. Facilitating Intangible Asset Finance:

Related is the difficulty of financing intangible investments, which remains a persistent obstacle, as conventional banking systems favor tangible collateral. Initiatives such as [InvestEU](#) and the [European Investment Fund \(EIF\)](#) could develop dedicated mechanisms for intangible-intensive SMEs, for instance through valuation models that recognize intellectual property, portfolios, and data assets as bankable resources.

5.4.2| Rethinking Innovation Policy Instruments: Function-Based Interventions

The results presented in this dissertation argue for a new generation of function-based policy instruments that complement and refine existing sectoral and national tools. These instruments should recognize that the functional composition of economic activity also determines innovation capacities (at least of industries). Three interrelated domains emerge as particularly relevant.

4. Aligning Horizon Europe Missions with Functional Specialization

[Horizon Europe](#) already embraces a mission-oriented approach to addressing “grand societal challenges.” However, the evidence presented here suggests that missions could be further strengthened by integrating a functional perspective. Specifically, funding calls could prioritize projects that combine pre- and post- production functions, whilst still maintaining diversity.

In addition, EIC funding instruments such as the Accelerator, the Pathfinder, and the Transition programs could explicitly support firms that submit projects based on a ‘multiplicity’ of economic activities, rewarding those that integrate, for example, design, production, and service functions across borders. This would be particularly relevant for the KIBS and service firms, where functional diversity is a proven driver of innovation capacity.

5. Embedding Functional Logic into Smart Specialization Strategies (S3)

Regional innovation policy in the EU, in part through [Smart Specialization Strategies](#), has achieved significant progress by encouraging regions to focus on their comparative advantages. Yet most S3 frameworks remain sectorally oriented. The functional evidence developed here suggests that S3 could evolve toward a “Smart Functional Specialization” (SFS).

Such an approach would identify not only *what* sectors a region is strong in, but *which functions* it performs competitively. For instance, Southern European regions could position themselves as hubs for innovation-intensive post-production activities, while Northern and Western European regions could deepen their specialization in R&D and digital pre-production. This would enable regions to integrate more effectively into GVCs without competing solely on cost or scale; again, with the caveat that hyper specialization or ‘exclusive deepening’ might in the long term leads to value and innovation capacity loss.

6. Integrating Functional Insights into Cohesion and Industrial Policy

The EU’s [Cohesion Policy](#) and the general Industrial Strategy for Europe emphasize the so-called “twin transitions”—green and digital—as levers of inclusive growth. Functional specialization analysis can directly inform the targeting of these instruments. Cohesion funding could prioritize investments that strengthen underrepresented functions in lagging regions or hyper specialized industries, thereby incentivizing diversification in Services and deepening in Manufacturing, for example. Likewise, the

[Just Transition Fund](#), which actively supports, in their own words, “economic diversification,” could support the retraining and mobility of workers based on revealed specialization-innovation links in specific economic region and industries.

5.4.3 | Promoting Functional Diversification in Service Sectors

The empirical results demonstrate that functional diversification is a key determinant of innovation in service industries. This insight should guide the design of service sector innovation policies, which historically have received less attention than manufacturing.

The [European Innovation Scoreboard](#) could be expanded to incorporate functional metrics, while EU-level programs such as [Digital Europe](#) and [Creative Europe](#) could prioritize cross-functional collaborations among SMEs in popular areas like digital marketing and cultural production. These initiatives could foster the kind of combination of intangible assets that this dissertation and past scholars have identified as important for service-based innovation capacity.

5.5 | Final Reflection on European Economic Sovereignty

The insights from this research have some important implications for recent discussions on European [Open Strategic Autonomy](#) (OSA):

Specifically, the ‘strategic autonomy’ part refers to an inward-looking policy agenda forced upon Europe by an increasingly unreliable reliance on trade for critical resources. The need for this had been present for decades as Europe grew dependent on the USA and its neighbors for fuel and defense. However, it has been exasperated lately due to the Covid Pandemic and the shifting USA trade policies, as well as the Russia-Ukraine and USA-Iran wars, which all greatly affected, and continue to affect, energy supply and, thus, consumer prices, as well as European defense and security, motivating energy, technology, and defense sovereignty amongst policymakers.

The ‘open autonomy’ part intends to say this shift Europe is undertaking differs from traditional protectionism or isolationist strategies. Instead, it encompasses bilateral deals with various trade partners to lessen the dependence on any one region or nation for any critical resource or commodity and rule-based multilateral deals intended to combat unfair trade policies by would-be or past trade partners. Open Strategic Autonomy reflects European policy desires for greater economic and political sovereignty, and legal proposals are expected to continue to formalize this desire.

The ideas and data presented in this PhD dissertation, which examines Europe’s 5 biggest economies in terms of their functional profiles, functional change, and innovation propensities, have significant bearing on this process. Assuming the onus of production will fall on the private sector, the idea of decreasing reliance on outside energy and security means developing these capabilities internally. In other words, transitioning to Open and Strategic Autonomy means exceptional functional diversification. The results of this dissertation support this generally, but given the discussion in Chapter 4, they do so with some caveats.

Developing new functional positions, especially scale intensive industries like energy, could be associated with significant innovation stagnation, especially if there are no related functional specializations already in existence. As such, if the goal is European not national autonomy, it would be wise to strategically allocate new economic activities based on the existing size and innovation performance of, particularly, scale intensive economic sectors. However, a balance must be located as a divide between the functional profiles of Western and Mediterranean Europe already exists and should probably not be encouraged to grow for reasons related to socio-economic cohesion.

The problem, however, is that the pattern witnessed by the Mediterranean economies of Europe is that of oscillation (hyper specialization) in intangible- (tangible-) intensive functions relative to Germany and Holland. As such, the realization of OSA will likely fall to Western Europe (the Med) in terms of the intangible-intensive (tangible-intensive) functions required. **As such, OSA should be expected to deepen an already growing divide between Western Europe and the Mediterranean region.** This is a move in the wrong direction if the stated goal is continental not national autonomy. The challenge, therefore, for policymakers working on legally activating OSA is not to entrench divisive patterns such as “Europe’s Mediterranean factory” and the “Western European Hub” whilst at the same time realistically accounting for the capabilities of regions to secure functional positions in drastically different functions and areas.

Chapter 5 References

- Archibugi, D., & Lundvall, B. A. (Eds.). (2002). *The globalizing learning economy*. OUP Oxford.
- Blazek, J. (2016). Towards a Typology of Repositioning Strategies of GVC/GPN Suppliers: The Case of Functional Upgrading and Downgrading. *Journal of Economic Geography*, 16(4), 849-869
- Cohendet, P. & Simon, L. (2017). Chapter 3: Concepts and Models of Innovation. In Bathelt, H., Cohendet, P., Henn, S., & Simon, L. *The Elgar Companion to Innovation & Knowledge Creation* (Pp. 33-55). Edward Elgar publishing Cheltenham, UK • Northampton, MA, USA DOI 10.4337/9781782548522
- Corrado, C., Hulten, C., & Sichel, D. (2005). Measuring Capital and Technology: An Expanded Framework. In *Measuring Capital in the New Economy*. Chicago: University of Chicago press, 11-46
- Corrado, C., Hulten, C., & Sichel, D. (2006). Intangible Capital and Economic Growth. NBER Working Paper 11948
- Coveri, A., Paglialunga, E., & Zanfei, A. (2024). Functional Specialization & Upgrading in European Regions: New Insight from FDI Data. Working Paper series 2401, 1-27, University of Urbino Carlo Bo, Department of Economics, Society & Politics
- De Marchi, V., Giuliani, E., & Rabellotti, R. (2017). Do Global Value Chains Offer Developing Countries Learning and Innovation Opportunities? *The European Journal of Development Research*, 30(3), 389-407
- Ernst, D. (2009). A new geography of knowledge in the electronics industry? Asia's role in global innovation networks. *Asia's Role in Global Innovation Networks (March 6, 2009)*. East-West Center Policy Studies series, 54
- Gereffi, G. (1994). The organization of buyer-driven global commodity chains: how US retailers shape overseas. *New York*
- Humphrey, J., & Schmitz, H. (2002). How does insertion in global value chains affect upgrading in industrial clusters?. *Regional studies*, 36(9), 1017-1027
- Morrison, A., Pietrobelli, C., & Rabellotti, R. (2008). Global Value Chains and Technological Capabilities: A Framework to Study Industrial Innovation in Developing Countries. *Oxford Development Studies*, 36(1), 39-58. <http://dx.doi.org/10.1080/13600810701848144>
- Nelson, R. & Winter, S. (1982). *An Evolutionary Theory of Economic Change*. Cambridge, Mass.: Harvard University Press
- Teece, D. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6), 285-305. [https://doi.org/10.1016/0048-7333\(86\)90027-2](https://doi.org/10.1016/0048-7333(86)90027-2)
- Timmer, M., Miroudot, S. & de Vries, G. (2019). Functional Specialisation in Trade. *Journal of Economic Geography*, 19(1), 1–30. <https://doi.org/10.1093/jeg/lby056>