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Corso di Laurea Magistrale in International Economics and Commerce

THE IMPACT OF R&D INVESTMENT ON FIRM PRODUCTIVITY: A COMPARATIVE ANALYSIS ACROSS COUNTRIES

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Anno Accademico 2024 – 2025

Abstract

This thesis investigates the relationship between R&D investment and firm-level productivity across the United States, the European Union, Southeast Asia, and China over the period 2004–2019. By estimating an augmented production function through Fixed Effects models, the analysis aims to isolate the contribution of R&D to productivity, with a specific focus on the structural changes occurred during the post-crisis recovery (2009–2019).

The econometric evidence unveils asymmetries in the efficiency of R&D investments among the considered regions. While the findings confirm a consolidated technological leadership in specific advanced economies, they also highlight complex evolutionary patterns for the European and Asian contexts. In particular, the comparison between the long-run and the post-crisis period suggests that the responsiveness to innovation is not uniform but deeply influenced by underlying industrial structures and sectoral specialization.

The study ultimately addresses the productivity gap, offering empirical support to the "structural burden" hypothesis and questioning whether increased R&D spending automatically translates into productivity gains in the absence of a favourable sectoral composition.

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Introduction

In recent decades, the global economic landscape has undergone a profound structural transformation, marking the transition from a traditional industrial model, based on physical capital accumulation, to a knowledge-based paradigm. In this new scenario, intangible assets and specifically Research and Development (R&D) are no longer just secondary activities. Instead, they have become the key factors for long-term growth and competitiveness.

Economic theory has formalized this shift through the development of endogenous growth models. Seminal to this field is the work of Zvi Griliches (1979), who introduced the concept of the "Knowledge Production Function". According to this framework, the stock of knowledge accumulated by firm acts as an additional productive input within the standard production function, operating alongside traditional factors such as labour and physical capital. The theoretical expectation is straightforward: an increase in R&D stock should translate directly into an expansion of the production frontier, thereby enhancing firm productivity.

However, empirical evidence suggests that this relationship is neither linear nor uniform. While the consensus on the benefits of innovation is robust, the magnitude of R&D impact varies significantly depending on the industrial sector, firm size, and geographical context. As highlighted in the literature, high-tech sectors often exhibit different returns compared to mature industries, and the ability to transform research into productivity can differ between established Western economies and emerging Asian markets.

In this context, the present thesis aims to provide a comprehensive analysis of the impact of R&D investments on firm productivity through a comparative perspective. The study investigates the heterogeneity of research returns across four distinct geographical areas: the United States, the European Union, Southeast Asia, and China. The primary objective is to verify whether the R&D-productivity link is homogeneous across these regions or if structural divergences emerge, reflecting different stages of technological maturity and industrial specialization.

The empirical analysis relies on a balanced panel dataset taken from the European Commission's "EU Industrial R&D Investment Scoreboard". The dataset covers a broad time horizon from 2004 to 2019, allowing for a long-run assessment of productivity dynamics. Additionally, the study isolates the sub-period 2009–2019 to evaluate the stability of R&D returns in the post-crisis era, assessing how firms adapted their innovation strategies following the 2008 global financial shock. From a methodological standpoint, the thesis adopts an augmented Cobb-Douglas production function. To construct reliable capital stocks, the Perpetual Inventory Method (PIM) is applied, carefully addressing issues of obsolescence and depreciation. The econometric strategy addresses the unobserved heterogeneity typical of panel data by comparing Pooled OLS estimators with Fixed Effects (FE) models, while also controlling for time-invariant firm characteristics and common macroeconomic shocks via time dummies.

The study is structured to provide a logical progression from theory to empirical evidence. It begins with Chapter I by establishing the theoretical backbone of the research, reviewing the literature on the “residual” productivity and the evolution of the Knowledge Production Function. This theoretical review delves into empirical evidence at both sectoral and enterprise levels, discussing the role of firm heterogeneity, and measurement challenges.

Subsequently, Chapter II details the dataset and the econometric methodology, describing the features of the 2024 EU Industrial R&D Investment Scoreboard and the data preparation process.

Finally, Chapter III presents and discusses the econometric findings. Through a detailed breakdown of the R&D effect, the analysis comes up with cross-country and cross-sector comparisons, highlighting the structural differences between Western and Asian economies and identifying the specific drivers of productivity growth.

Chapter I

R&D AND PRODUCTIVITY: LITERATURE REVIEW

This chapter explores what the existing literature tells us about how R&D spending helps firms become more productive. It focuses on how ideas and knowledge, once created inside firms, are turned into better performance and higher growth, moving from early views of technology as an unexplained "residual" to more recent approaches that put innovation at the centre of firms' strategic decisions.

1.1 The concept of productivity as a "residual"

"Productivity isn't everything, but in the long run it's almost everything." To paraphrase Paul Krugman's famous insight, the ability of an economic system to improve its standard of living depends almost entirely on its ability to increase output per unit of input. At the heart of this dynamic lies technological innovation, the engine that allows us to shift the frontier of production possibilities. Historically, understanding this phenomenon has gone through several phases.

In the original neoclassical growth model, developed by Robert Solow (1957), technical progress appeared as a residual variable, exogenous to the system. Solow broke down economic growth into contributions from the accumulation of physical capital and labour; what remained unexplained a substantial portion of real growth was labelled "residual." As carefully observed by Moses Abramovitz (1956), this residual represented a “manna from even” or a “black box”, a statistical container into which organisational efficiency, the improvement of human capital and, above all, technological innovation converged. The aim of modern research is precisely to reduce Abramovitz's “ignorance” and then, to explain the residual by endogenous technological change. The latter it assumed to be mainly the fruit of investments in Research and Development.

The transition from theoretical concept to empirical measurement requires us to define precisely what we mean by “efficiency” and which indicator to use to approximate innovation. The key concept for assessing the impact of innovation is Total Factor Productivity. Historically defined by Abramovitz (1956) as the “measure of our ignorance” and formalized by Solow (1957), the “residual” of growth, TFP is the standard indicator of technical efficiency. According to the guidelines of the OECD (2001; 2007), TFP growth captures improvements in input quality and technological progress. In our framework, the introduction of R&D stock is important to explain this residual: we expect firms with greater knowledge stock to show higher TFP.

Just to clarify the concepts just expressed, we need to start from the standard production function where output (Y) is determined by Technology (A), Physical Capital (C) and Labor (L)[1].

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[1] $Y = AC^{\alpha}L^{\beta}$. Cobb-Douglas production function

The production function, a concept that we will explore further in the following paragraphs, expressed implicitly, looks like this: $\mathrm{Y} = \mathrm{TFP}\ \mathrm{f(K, L)}$. Where TFP is calculated directly by observing the growth of the other variables. By transforming the equation, applying logarithms, and considering changes over time, we obtain the Growth Accounting equation (Solow 1957).

$$\frac{\Delta A}{A} = \frac{\Delta Y}{Y} - \left(\alpha \frac{\Delta K}{K} + \beta \frac{\Delta L}{L}\right),$$

- $\frac{\Delta A}{A}$ represents the growth rate of TFP.
- $\frac{\Delta Y}{Y}$ represents the growth rate of Y (output).
- The terms appearing within the brackets represent the contribution of physical capital and labour with their respective elasticities.

Thus, Total Factor Productivity is calculated by subtracting the growth of tangible input factors from the growth of total outputs. This difference is called residual. To best explain the residual, we must highlight an important concept: "technological progress is not only the result of exogenous factors but also of investments in Research and Development[2] undertaken by companies", which best explain the concept of innovation.

[2] TFP = g(A,K). K is a measure of the Knowledge capital stock or R&D capital stock

1.1.1 What is R&D?

In economics, the term “R&D spending” is associated with all those investments that companies, governments and institutions make in systematic activities to create new knowledge, products, processes or improve existing ones, aiming to innovate and increase competitiveness, stimulating economic growth.

According to the international standards laid down in the OECD Frascati Manual, Research and Development (R & D) activity is defined as “ the complex of creative work undertaken on a systematic basis with the aim of increasing the wealth of knowledge including knowledge of man, culture and society and of using that wealth to devise new applications.” Operationally, R&D is divided into three distinct but interconnected macro-categories:

“Basic research; this includes experimental or theoretical work carried out primarily to gain new insights into the foundations of observable phenomena and facts, without any specific application or intended use in the short term.

Applied research; while also an original investigation aimed at acquiring new knowledge, it differs from basic research in that it is primarily directed towards a specific practical objective or purpose.

Experimental development; this consists of systematic work that, building on existing knowledge acquired through research and practical experience, is aimed at producing new materials, products, or devices, installing new processes, systems, and services, or substantially improving those already produced or installed. R&D

data are collected through national statistical surveys covering both public and private entities and are classified according to the Revised Fields of Science and Technology, which include natural sciences, engineering and technology, medical and health sciences, agricultural sciences, social sciences, and humanities and arts." An accurate definition is essential to understand that the main object of the thesis and all the connections that will be shown in the subsequent paragraphs.

1.1.2 R&D evolution over time

To understand the current configuration of innovation investments, it is essential to analyse the historical evolution of R&D spending, taking as a reference the case of the United States, which has anticipated global trends. Historical data from the Congressional Budget Office (CBO, 2005) reveal that, although R&D spending has remained relatively constant relative to the size of the economy (varying between 2% and 3% of GDP since the 1960s), the composition of funding sources has undergone a radical transformation. Until the late 1980s, federal spending played a predominant role, driven primarily by investments in space programs and defence. However, analysing the subsequent period, the CBO (2005, pag. 1) notes that "a profound shift has occurred in the pattern of R&D investment during that time, a move away from federal spending and toward private spending." Indeed, while federal spending has plateaued, real growth in R&D investment (which has increased at an average annual rate of 4.6% since the early 1950s) has been driven almost entirely by the private sector. In 2003, for example, out of a total of 284 billion, as much as 70 percent was financed by private industry, marking the definitive overtaking of private capital over public expenditure. Analysing the composition of this private expenditure, the predominance of experimental development over pure research clearly emerges. The data show that “development makes up the largest share of private R&D spending: between 1953 and 2001, development averaged about 71 percent, followed by applied research (23 %) and basic research (5 %)” (CBO, 2005, pag. 10). This stability in shares suggests that the nature of corporate investment is structurally oriented towards practical and commercial application, rather than basic knowledge. Finally, historical evolution highlights a strong sectoral concentration, which anticipates the “Technological Dualism”[3] discussed in recent literature. Most private expenditure (around 60% in 2001) is taken up by manufacturing. Within this, the leadership of the High-Tech sectors can be observed already at the beginning of the millennium: “Among manufacturers, companies in the computer and electronics industries, including semiconductor manufacturers, accounted for the largest share (38 %), followed by companies in the transportation equipment (19 %) and chemical (16 %) industries” (CBO, 2005, pag. 10). These historical data confirm that the concentration of R&D

[3] The concept of “technological dualism” refers to the structural divergence in innovation mechanisms between industrial sectors. As highlighted by Ortega-Argilés, Piva and Vivarelli (2015), high tech sectors operate in a "cumulative growth" regime while low-tech or traditional sectors are mainly based on "embodied" technological change.

in specific high-tech sectors and the predominance of large private investors are not recent phenomena, but the result of a structural trend which has been consolidated in recent decades.

1.1.3 R&D contribution on productivity

To empirically assess the impact of innovation on economic growth, the methodology adopted in this study aligns with the standard approach described by the Congressional Budget Office (2005). The literature predominantly utilizes "econometric analysis" based on regression equations to estimate the specific effects of R&D changes on key economic variables such as "production costs, output, and productivity." These studies are typically categorized into two main approaches: "production function studies," which estimate the effect of R&D on output, and "cost function studies," which analyse the impact on production costs. Within the production function framework, which represents the most prevalent approach in the empirical literature and the one adopted in this thesis, it is possible to distinguish between:

- Cross-sectional studies, which examine differences among firms or industries at a single point in time.
- Time-series studies, which analyse changes in variables over time.
- Panel studies, which combine both dimensions by tracking the same set of entities (firms or industries) across multiple time periods.

The latter offers a methodological advantage, as it allows us to control for unobserved heterogeneity. As also explained by Griliches (1998), companies have several qualitative characteristics that are difficult to measure quantitatively, for example managerial quality, culture, and positioning. A crucial methodological choice is the reliance on econometric analysis rather than case studies or cost-benefit analyses. As noted by the CBO, while case studies offer deep insights, they are prone to significant selection bias because authors tend to select projects that turn out to be successful, which makes it difficult to generalize. Econometric studies provide a more rigorous quantitative assessment because they "incorporate all R&D projects [...] regardless of whether the projects are successful" (CBO, 2005, pag. 4). By including failed or non-profitable investments in the aggregate data, these studies avoid overestimating the returns to innovation, providing a more realistic picture of the "overall quantitative results" and the actual rate of return.

1.2 The Knowledge production function

The fundamental theoretical transition occurs with the advent of "New Growth Theory" (Romer, 1990; Aghion and Howitt, 1992), which transforms innovation from a godsend to the result of intentional economic decisions. In this context, the seminal contribution to the empirical analysis is due to Zvi Griliches (1979. Griliches formalizes a powerful concept: "Knowledge is not a stream of current expenditure, but a stock of capital."

Just as an enterprise accumulates physical capital through investments in machinery, it accumulates an intangible wealth of know-how, patents and innovations mainly through investments in R&D.

The functional relationship adopted is the augmented Cobb-Douglas:

$$Y_{it} = Ae^{\lambda t} C_{it}^{\alpha} K_{it}^{\gamma} L_{it}^{\beta}$$

Where:

- Y represents output (generally measured as Value Added or deflated Sales).
- C is the physical capital stock.
- L is the labour factor (number of employees).
- K is the R&D capital stock (knowledge).
- γ is the parameter of primary interest, representing the elasticity of output with respect to the R&D stock.
- $Ae^{\lambda t}$ captures disembodied technical progress and common exogenous shocks.
- i is an important parameter which indicates sector or firm.
- t indicates time (year).

In log-linear form, used for econometric estimation, the equation becomes:

$$y_{it} = a_i + \lambda t + \alpha c_{it} + \gamma k_{it} + \beta l_{it} + \varepsilon_{it}.$$

Where lower-case letters indicate the logarithms of the variables. The sum of the coefficients $\alpha + \beta + \gamma$ measures the returns to scale with respect to the three inputs. In this equation, the output (Y) depends on traditional factors and the knowledge stock (K). The parameter γ (the elasticity of output with respect to knowledge), tells us how much the firm's productivity increases if its stock of knowledge increases by a given percentage. The theoretical assumption is that γ is positive and meaningful: the firm that has a larger "warehouse of ideas" can produce new or better goods or supply the same goods at lower costs.

1.3 Empirical evidence: from sectors to enterprises

The validity of Griliches' model has been extensively tested. Two lines of research are particularly relevant for interpreting data: sector-level analysis and enterprise-level analysis.

1.3.1 Sectoral level analysis

To fully comprehend the dynamics of productivity, it is essential to move beyond aggregate analysis and adopt a disaggregated perspective, recognising that the relationship between R&D and Total Factor Productivity (TFP) is not uniform across industries. A pivotal contribution in this direction is provided by Sterlacchini and Venturini (2014), who argue that the intensity of R&D in a given industry is largely dominated by two key variables: "technological opportunity and the ability to appropriate returns from new developments" (Sterlacchini & Venturini, 2014, p.

361). Consequently, the authors note that "technological opportunities can be augmented or renewed at a higher rate" (Sterlacchini & Venturini, 2014, p. 362) only in specific science-based sectors, whereas traditional industries face structural limitations in this regard.

The empirical evidence confirms this dichotomy. In their dynamic panel analysis comparing Italy and Spain, Sterlacchini and Venturini (2014) demonstrate that "knowledge capital turns out to be a significant driver of productivity only for R&D-intensive industries" (Sterlacchini & Venturini, 2014, p. 372). Conversely, for medium- and low-tech industries, the link between internal research and productivity growth is weak or non-existent. As noted by the authors, the productivity growth of the so-called medium- and low-tech industries "will not be based on R&D but on other types of investment" (Sterlacchini & Venturini, 2014, p. 362), such as the accumulation of physical capital or the adoption of technologies embodied in machinery purchased from upstream sectors.

This sectoral heterogeneity is crucial for explaining cross-country productivity differentials. In an earlier extensive study covering five OECD countries, Sterlacchini and Venturini (2007) highlight that the superior performance of the United States is strictly linked to its leadership in high-tech sectors. Their estimates show that the long-run elasticity of TFP with respect to R&D capital is highest in the US (0.51), driven by the exceptional performance of the "Electrical & Optical Equipment" industry, which includes the bulk of ICT products and "has been one of the main driver of the productivity revival experienced in the US" (Sterlacchini & Venturini, 2007, p. 14).

In contrast, the lower elasticity found for Italy (0.14) is not merely a result of its specialisation in traditional sectors, but rather of a slowdown in accumulation. The authors observe that "the weak relationship between R&D and TFP arising for Italy is not due to structural [...] features but is the outcome of a decade of slowdown in R&D investment" (Sterlacchini & Venturini, 2007, p. 4).This evidence reinforces the thesis that, to close the productivity gap, "the high-tech industries of the EU should substantially increase their R&D investment" (Sterlacchini & Venturini, 2007, p. 4), as aggregate spending alone is insufficient without a targeted expansion in sectors with high technological opportunities.

1.3.2 Enterprise level analysis

Shifting the attention to the individual firm, the work of Ortega-Argilés, Piva and Vivarelli (2015), represents the modern benchmark. The authors document a phenomenon of "Technological Dualism" as previously mentioned.

Their econometric results show that the elasticity of R&D (γ) is not uniform. In the High-Tech sectors, the coefficient is high and highly significant, confirming the hypothesis of increasing and cumulative returns. In contrast, in Low-Tech sectors, the impact of R&D on productivity is often nil or statistically negligible. Interpreting these results, the authors claim that companies in high-tech sectors have greater technological opportunities and greater absorptive capacity, which allow them to translate knowledge investments into efficiency gains more effectively than traditional sectors. This result contrasts with the “later comer advantage” hypothesis. The concept of latecomer advantage is particularly relevant for the analysis of emerging economies like China. Although theory suggests that follower countries can grow faster by adopting existing technologies, recent data show a more complex scenario. On the other hands, Ortega-Argilés, Piva and Vivarelli, demonstrate that technologically advanced sectors are “still ahead,” suggesting increasing returns in knowledge production due to greater technological opportunities. This result is fundamental for our thesis: we expect the R&D-Productivity link to be strong for pharmaceutical or IT companies, but weak for automotive or steel companies, which rely more on process innovations embedded in physical capital. Just as a company accumulates machinery, plant, and equipment (physical capital) to produce goods, it also accumulates over time an intangible asset of discoveries, know-how, and proprietary technologies (knowledge capital) through periodic investments. In this model, the company's output becomes a function of traditional factors (labour and physical capital) augmented by the accumulated stock of knowledge. The theoretical objective is to demonstrate that, all other inputs being equal, a company with a larger stock of knowledge can operate more efficiently.

Another important analysis to consider is that of Robert Wieser (2005). The author conducts a survey of 52 different empirical studies published between 1965 and 2000, covering a wide range of OECD countries. His work provides a solid statistical basis for establishing what constitutes a normal return on innovation. Analysing the aggregate results, R&D has a positive and significant impact on productivity, with an estimated median elasticity of around 0.13. This implies that, on average, a 10% increase in research and development stocks leads to a 1.3% increase in productivity. However, Wieser highlights a crucial methodological divergence that is consistent with our previous discussion: cross-sectional studies consistently produce higher elasticities than time series studies. This suggests that while R&D represents a powerful discriminant between successful and unsuccessful companies in the long run, capturing its immediate impact on annual growth is more difficult because of delays and adjustment costs. The extent of the economic contribution of R&D appears particularly in the analysis Leo Sveikauskas (2007). The author goes beyond simple elasticity to analyse the rate of return on investments, using a metric comparable to financial assets. However, the author, through his analysis, manages to understand that the private rate of return on R&D typically stands between 20% and 30%, a significantly higher figure than the return on physical capital. Furthermore, another key point of his analysis is to highlight the distinction between private and social returns. Because companies fail to fully internalize the benefits of their ideas, social returns (which include effects on other companies) may be two to three times higher than private returns, often exceeding 50%. Accordingly, we can say that R&D is not simply a cost, but the most productive resource a company can accumulate, generating value not only for the individual company but for the entire economy.

1.3.3 Size and sectoral heterogeneity

Heterogeneity concerns not only sectors but also the Firm's size. The study of Montresor and Vezzani (2015) provides crucial insights for our study. By applying quantile regression techniques to data from the EU Industrial R&D Investment Scoreboard (the same dataset used in this thesis), the authors demonstrate that the production function is not homogeneous but varies along the dimensional distribution of firms.

Their results indicate a structural dichotomy that standards OLS regressions fail to capture:

- Input Elasticity; especially in High-Tech sectors, knowledge capital proves to be the input with the highest return, consistently outperforming physical capital regardless of firm size. In contrast, in medium-low technology sectors, physical capital remains the predominant factor driving productivity, while R&D plays a secondary role.
- Return to scale; the study reveals that returns to scale are "bounded by the size of the firm", but this constraint depends on technological intensity. In

traditional sectors, return to scale tend to decrease as firms get larger, suggesting a natural limit to growth based on physical accumulation. However, this trend disappears in High-Tech sectors: here, innovation acts as a lever to mitigate diminishing returns, allowing firms to sustain growth even at the “top of the top” scale.

1.4 Econometric methods and spillovers

An important fact that comes from the comparative econometric literature is the systematic divergence in results depending on the estimator used. Classic studies such as those by Griliches and Mairesse (1984) for the US-France comparison, and Harhoff (1998) for Germany, show a recurring pattern:

- Cross-section estimates (which compare the productivity of different firms each year) produce high and significant R&D elasticity coefficients (typically between 0.10 and 0.20) as they capture long-term structural between firms.
- Time-series or fixed effects estimates (which observe the evolution of the same firm over time) produce much lower elasticities (often in the range of 0.02-0.08) and sometimes insignificant ones.
- When using Pool OLS estimates on panel data, i.e., ignoring firm specific effects and treating all observation as independent, the coefficients tend to approach the high values obtained in cross-section estimates. This implies

that strong structural heterogeneity prevails in the data across firms, which could influence parameter estimates.

The reasons for this decline, discussed by Griliches (1998) and the CBO (2005), are two. On one hand, the Fixed Effects technique, by removing the variance between companies, tends to amplify the weight of measurement errors in the data (attenuation bias). On the other hand, there is a problem of time lags: the CBO (2005) notes that the full benefits of R&D on productivity may emerge even after 5-10 years, a long-term horizon that models based on annual variation struggle to capture fully. Nevertheless, as suggested by Scott (1984) and Levin and Reiss (1984), ignoring unobserved heterogeneity (such as the specific managerial quality of the firm) would lead to biased results.

Therefore, the Fixed Effects model remains an essential component of the estimation strategy.

1.4.1 Spillovers: private vs social returns

It is essential to recognise that the microeconomic analysis conducted in this thesis captures only the private returns of innovation, i.e., the productivity gains appropriable by the investing firm. However, knowledge has the characteristics of a partial public good. Griliches (1992) distinguishes between:

- Rent Spillovers, as monetary benefits transferred to customers through prices that do not fully reflect the improvement in quality.

- Knowledge Spillovers, as actual flows of ideas that are imitated or reworked by third parties ("Technology Flow").

The review by Sveikauskas (2007) clearly quantifies this discrepancy. Comparing numerous empirical studies, Sveikauskas highlights that while private rates of return typically stand at around 25%, social rates of return (which include inter-industry spillovers) reach levels close to 65%. This implies that the estimates presented in this paper necessarily represent a lower bound of the real economic contribution generated by investments in innovation.

1.5 Limits of the approach based on production function

However, it must be recognised that the Cobb-Douglas function represents a simplification of reality. It assumes, for example, a unitary elasticity of substitution between factors and struggles to capture the dynamics of Schumpeterian "creative destruction," where innovation does not simply improve existing efficiency, but makes old products obsolete.

1.5.1 The problem of "double counting"

Another crucial methodological issue raised by Hall and Mairesse (1995) is the correction for "double counting". R&D expenditures reported in financial statements include costs for high-skilled employees (e.g. researchers) and materials or machinery that are already accounted for in the traditional variables of Labor and Physical Capital. Without a correction that subtracts the share of inputs dedicated to research from variables (L) and (C), R&D elasticity estimates would be biased downwards.

1.5.2 Scope of the study: R&D vs. ICT

Before proceeding, a fundamental distinction must be made regarding the scope of this study. The frontier of today's literature adopts increasingly multifactorial approaches, as highlighted by Lotti, Hall, and Mairesse (2013), traditional R&D is no longer the only driver of productivity growth. The latter is often maximised by the complementarity between internal research and investments in Information and Communication Technologies and organisational capital. Lotti et al. show that, especially for medium-tech enterprises, the adoption of digital technologies has an impact on Total Factor Productivity (TFP) comparable to or greater than that of R&D. Despite this, for the sample of large multinationals analysed in this thesis, R&D remains the most robust metric for capturing the shift in the technological frontier.

1.6 Measurement challenges: indicators and depreciation

1.6.1 Input vs. Output: R&D expenditure vs Patents

But which variable should be used to measure this stock of knowledge? The literature has historically been divided between two approaches, as extensively explained by Griliches (1984; 1998).

The first approach is the Innovation Output (Patents), which would seem to be the most direct measure of inventive success. What is patent? According to World Intellectual Property Organization (WIPO), “A patent is an exclusive right granted for an invention.” What about invention? As suggested by the same institution (WIPO), “an invention is a product or a process that provides a new way of doing something or offers a new technical solution to a problem that surpasses trivial solutions.”.

Using a large panel of 2,500 U.S. manufacturing firms, bound et al. (1984) demonstrate that, although there is a strong contemporary correlation between R&D and patents, the relationship is nonlinear and exhibits systematic biases related to firm size:

- The Size Effect: the authors find that small firms show a significantly higher propensity to patent than large firms. The Patent/R&D ratio tends to decrease as the research budget increases. This suggests that “Top Investors” use different intellectual property protection strategies, relying more on industrial secrecy, lead time, or the exploitation of economies of scale and networks, rather than legal patent protection for each individual innovation.
- Statistical “Noise”: while R&D spendings of large enterprises tends to be a stable and persistent historical series over time (enterprises plan long-term budgets), the patent count is extremely volatile and "noisy". Many

incremental innovations are not patented, and the economic value of the patents granted is highly asymmetric (very few are worth much, the majority have zero value), as also confirmed by Pakes and Griliches (1984).

The second approach is the Innovation Input (R&D Expenditure). To overcome the limitations of patents, the econometric literature on productivity (Hall & Mairesse, 1995) converges on the use of R&D expenditure. Although it measures effort rather than results, for the large multinational companies covered by this thesis, it represents the most stable, comparable, and reliable metric of strategic commitment to innovation. However, the use of R&D as an input is not without its problems. Schuhmacher et al. (2023), analysing the productivity of the pharmaceutical sector, document the so-called "Eroom's Law" (the inverse of Moore's Law): the R&D cost required to discover a new approved drug doubles approximately every 9 years. This suggests that, especially in some mature high-tech sectors, there are diminishing returns on research investments.

1.6.2 Obsolescence and depreciation

A final crucial aspect concerns the nature of the stock of knowledge. Unlike physical capital, which depreciates largely due to wear and tear, knowledge capital is a durable asset subject to economic obsolescence. This depreciation is driven primarily by the "creative destruction" process; the technological progress of competitors and changes in market preferences render older knowledge less valuable over time. Although the calculation methodology (Perpetual Inventory Method) will be detailed in subsequent chapters, it is essential to highlight the empirical evidence on decay rates here to justify our modelling choices.

Conventionally, a uniform depreciation rate of 15% is widely accepted in the literature, following the standard "rule of thumb" established by Hall and Mairesse (1995). However, empirical studies focusing on the lifespan of intellectual property suggest that reality is more complex. Pakes and Schankerman (1984), analysing data on patent renewals, where the cessation of renewal fees indicates that the patent's value has fallen below the cost of maintenance, estimated that the private value of innovation declines at a significantly faster annual rate, ranging between 15% and 25%.

Furthermore, homogeneity across industries cannot be assumed. Subsequent studies by Harhoff (1998) on German manufacturing firms provide compelling evidence of sectoral heterogeneity. Harhoff suggests that in High-Tech sectors (such as IT or electronics), the depreciation rate may be significantly higher than the standard 15%, potentially reaching 30-40%, due to extremely rapid product life cycles and intense competitive pressure. Conversely, low-tech sectors may exhibit slower obsolescence. Consequently, to capture these dynamics more accurately, in my empirical analysis I will depart from a flat rate and instead apply differentiated depreciation rates by sector, assigning higher rates to high-technology industries.

1.6.3 The innovation paradox

Although economic theory has made great strides, evolving from Solow's (1957) exogenous growth models where technical progress was treated as an unexplained "residual" to the endogenous "New Growth Theory", recent empirical evidence presents us with an unexpected scenario. Intentional investments in R&D have been placed at the centre of wealth accumulation.

However, referring to the work of Akcigit (2024), caution is needed, the quantitative increase in investment in emerging economies does not automatically translate into efficiency if the allocation of resources is distorted by structural inefficiencies.

In his recent work, Akcigit documents a worrying case; despite unprecedented aggregate investment in R&D (driven by the technological race between the United States and China), global productivity growth is stalling, showing a structural slowdown. The author attributes this phenomenon to the strategic behaviour of large companies, which often use innovation not to generate radical advances, but to "defend" their market position, effectively reducing technological diffusion.

To understand this phenomenon, it is therefore necessary to disaggregate the analysis at the microeconomic level, investigating how individual companies accumulate, manage, and transform knowledge into productive efficiency.

Chapter II

DATA AND METHODOLOGY

This chapter describes the database used for the empirical analysis and the econometric strategy adopted. First, the features and main findings of the "EU Industrial R&D Investment Scoreboard" are presented, discussing the geographical and temporal coverage of the sample and potential biases related to the nature of the data. Subsequently, the data preparation and cleaning process is detailed, with particular emphasis on the sectoral normalization procedure and the application of the Perpetual Inventory Method for constructing physical and knowledge capital stocks. Another important argument is the econometric strategy, deriving the estimation equation from the theoretical model and comparing Pooled OLS and Fixed Effects models, supported by Wald and Hausman diagnostic tests. Finally, the main challenges and limitations of the database are discussed, and, to complement the analysis, sectoral R&D intensities are also illustrated by comparing descriptive statistics across countries and sectors.

2.1 The Industrial R&D Scoreboard

The empirical analysis relies on microdata extracted from the "EU Industrial R&D Investment Scoreboard", published annually by the Joint Research Centre of the European Commission. This database monitors the world's top corporate R&D

investors, ranking companies based on the nominal amount of R&D investment financed by their own funds. Financial data are extracted from audited consolidated accounts, ensuring a high standard of reliability and international comparability.

2.1.1 Main findings from the 2024 Scoreboard

The descriptive analysis of the most recent data, taken from the 2024 edition of the EU Industrial R&D Investment Scoreboard, offers a complete framework for understanding the context in which the companies analysed in this study operate. The last edition of the Scoreboard considers the world's top 2000 companies which alone, account for about 90% of global private sector-funded R&D spending.

Despite a macroeconomic environment characterized by uncertainty and political tension, global investment in innovation has not stopped. In 2023, the Scoreboard companies invested a record €1,257.7 billion, a net increase of €90.6 billion compared to the previous year.

2.1.2 Country and sectoral ranking

Geographically, the data show interesting short-run changes. While maintaining the United States' global leadership in absolute investment volume, the European Union highlighted strong growth. For the first time since 2013, European companies recorded a growth rate of R&D investment of +9.8%, higher than that of both US companies (+5.9%) and Chinese companies (+9.6%). Europe thus strengthens its position as the world's second largest investor, managing to maintain its lead over China, which is showing a slowdown for the first time in years.

The data shows that four macro-sectors alone absorb the main part of all global R&D spending: ICT Hardware, ICT Software, Pharmaceutical & Biotechnology and Automotive specialization in the ICT manufacturing sector.

2.1.3 Geographical coverage

The study adopts a comparative approach, analysing four distinct macro-geographic areas to capture structural differences in research returns.

First, United States, which represents the technological frontier and the main benchmark. Other important macro-geographic area is European Union; it includes companies with registered headquarters in the 27 Member States (plus the United Kingdom for the period considered). East Asia in addition to Japan, this category includes mature or advanced economies in Southeast Asia, specifically South Korea, Taiwan, and Singapore, characterized by high technological intensity.

Finally, China, the emerging economy that has shown the highest R&D investment growth rates in the last decade.

2.1.4 International technological division

Finally, the data underline a clear international division of innovation. The United States continues to dominate in science-based sectors, such as ICT services driven by large software players and healthcare, confirming a specialization in intangible technologies. The European Union maintains global leadership in the automotive sector, which accounts for the largest share of the continent's R&D investment, with the need to support the transition to electric mobility. Finally, China, which consolidates its role as “the world's technological factory”, with a marked specialization in the ICT manufacturing sector.

2.2 The Scoreboard panel

By using the Scoreboard panel our analysis covers a 16-year time horizon, from 2004 to 2019. Furthermore, a specific analysis is conducted on the subperiod 2009-2019 to isolate the post-financial crisis dynamics and verify the resilience of innovation returns in a changed economic context.

The Scoreboard was first born in 2004, as a large data container for all the top World companies investing in R&D. Every year, new data on new businesses were published, starting from a minimum number of 1000 for EU and non-EU businesses up to 2,500. From 2011, the data provider changed from Company Reporting to Bureau van Dijk, generating a strong transition. The Scoreboard then became a historical data container, also called the Vintage Scoreboard. This change allowed for the inclusion of important financial data for companies, covering a long-time span. The final dataset contains a total of 6215 companies in the period 2003-2022, resulting in a total of 72.899 observations.

2.3 Data preparation and cleaning

Construction the final database required a rigorous cleaning and variable treatment procedure to ensure the robustness of econometric estimates.

2.3.1 Variable definitions

The key variables used in the analysis are:

- Net Sales (Y): Used as a proxy for output, deflated using the country-specific GDP deflator (base year 2015).
- Employees (L): The average number of employees during the year, used as a measure of the labour factor.
- R&D Investments (R): Annual flows of research and development expenditure deflated, used to build the knowledge capital stock (K).
- Capital Expenditures (*Capex*): Investments in tangible assets deflated, used to build the physical capital stock (C).

2.3.2 Treatment of outliers and missing values

To avoid distortions, observations presenting null or negative values for key variables (Sales, R&D, Capex, Employees) were excluded from the sample. Additionally, a filter was applied to remove extreme outliers, such as companies with anomalous Capex/Sales ratios (e.g., negative or excessively high values due to extraordinary operations), following the standard procedures described by Hall and Mairesse (1995). A further source of distortion concerns firms with R&D

intensity above 100%, i.e. cases in which reported R&D expenditure systematically exceeds sales over the reference period. These observations were treated as clear outliers and removed from the panel, together with firms showing more than eight years with such extreme R&D intensity values. Almost all of these cases are concentrated in the US Pharmaceutical & Biotechnology sector, with only a few additional European firms, suggesting that in these sectors some newly established firm invest heavily in R&D before achieving substantial sales.

2.3.3 Sectoral normalization

A critical issue emerging during preliminary data analysis concerns industrial classification. Some companies, despite presenting continuous data, are classified in different sectors depending on the survey year (e.g., a company classified as "Technology Hardware & Equipment" in 2010 and "Media" in 2015).

This phenomenon poses a severe methodological problem for calculating capital stock via the Perpetual Inventory Method (PIM), as the depreciation rate (δ) depends on the sector of belonging. If the sector changes over time, the applied δ also changes, introducing artificial discontinuities in the stock series.

To resolve this issue, a sectoral normalization procedure was adopted: each company was assigned to a unique sector for the entire period considered, based on the mode (the sector in which the company was classified most frequently) or, in case of a tie, the latest available classification. This ensures the temporal consistency of depreciation parameters.

2.3.4 Calculation of capital stocks

Unlike the labour factor, the stock of knowledge is not directly observable in company financial statements, which usually report only annual R&D expenditure flows. Similarly, to ensure methodological consistency across the different geographical areas analysed (USA, EU, Japan, Singapore, Taiwan, Soth Korea and China), it is necessary to reconstruct the Physical Capital stock starting from investment data (Capex). To overcome this problem, the literature adopts the Perpetual Inventory Method.

R&D (*K*) and physical (*C*) capital stocks were constructed by applying the PIM with differentiated depreciation rates based on the technological intensity of the sector, following the approach of Ortega-Argilés et al. (2015).

2.3.5 The perpetual inventory method (PIM)

According to the PIM, the stocks of R&D capital (*K*) and Physical Capital (*C*) at the beginning of period *t* (K_t) and (C_t) are defined as the sum of the stocks from the previous period, net of depreciation, plus R&D and Physical Capital investments made in the *t* period (R_t) and (I_t):

$$K_{it} = (1 - \delta_k)K_{it-1} + R_{it} \quad \text{and} \quad C_{it} = (1 - \delta_c)C_{it-1} + I_{it}$$

Where:

- R_{it} represents the R&D expenditure of firm i at time t.
- I_{it} represents the investment in physical capital (Capex).
- δ_k and $\delta_c$are the depreciation rates of knowledge capital and physical capital, respectively.

To calculate the initial stock (K_0 and C_0) in the absence of infinite time series, the formula introduced by Hall and Mairesse (1995) approximates the stock as the ratio between the initial investment and the sum of the depreciation rate and the historical growth rate (g). However, to avoid distortions deriving from arbitrary or volatile growth rates in different geographical regions, in this analysis, a growth rate g equal to zero was assumed. Therefore, the initial stock is calculated as:

$$K_{i0} = \frac{R_{i0}}{\delta_k} \quad \text{and} \quad C_{i0} = \frac{I_{i0}}{\delta_k}$$

2.3.6 The choice of depreciation rates

The choice of the depreciation rate δ is a critical parameter, as it reflects the speed at which knowledge or machinery becomes obsolete. Although the standard convention by Hall and Mairesse (1995) suggests a unique rate of 15% for R&D, recent studies highlight the need to differentiate depreciation rate according to the technological intensity of the sector.

Following the methodological approach of Ortega-Argilés, Piva, and Vivarelli (2015), in this study, differentiated depreciation rates were applied to capture the more rapid technological obsolescence in advanced sectors compared to traditional ones:

1) R&D Capital (δ_k):
   - 0.15 (15%) for low and medium-technology sectors.
   - 0.18 (18%) for high-technology sectors, reflecting a shorter innovation life cycle.
2) Physical Capital (δ_c):
   - 0.06 (6%) for low/medium-tech sectors.
   - 0.07 (7%) for high-tech sectors.

This differentiation allows for a more accurate estimation of the net capital stock effectively available to firms in different industrial sectors.

2.4 Econometric strategy

To estimate the elasticity of productivity with respect to R&D stock, the thesis adopts a sequential approach. Before describing the estimators used, it is essential to detail the mathematical derivation that leads from the theoretical model to the estimated equation.

2.4.1 From the theoretical model to the econometric specification

The starting point is the augmented Cobb-Douglas production function discussed in Chapter I. The first step to make the model linearly estimable consists of applying natural logarithms to both sides of the equation. This transformation allows interpreting the coefficients as elasticities:

$$\ln(Y_{it}) = a + \lambda t + \alpha \ln(C_{it}) + \gamma \ln(K_{it}) + \beta ln\ (L_{it}) + \ \epsilon_{it}$$

However, to focus the analysis on productive efficiency and mitigate potential heteroscedasticity issues related to firm size, the reference literature (Hall and Mairesse, 1995; Ortega-Argilés et al., 2015) suggests moving from a production function to a labour productivity function.

Mathematically, this is achieved by subtracting the logarithm of labour $(ln\ (L_{it})$ from both sides of the equation. Leveraging the properties of logarithms $ln(A) - ln(B) = ln\left(\frac{A}{B}\right)$, we obtain:

$$\ln(Y_{it}) - \ \ln(L_{it}) = a + \lambda t + \alpha \ln(C_{it}) - \ \alpha \ln(L_{it}) + \gamma \ln(K_{it}) - \gamma \ln(L_{it}) + (\alpha + \beta + \gamma - 1) ln\ (L_{it}) + \ \epsilon_{it}$$

Rearranging the terms to express capital stocks in terms of intensity (per employee), we arrive at the final equation used in the econometric estimations of this thesis:

$$ln\left(\frac{Y_{it}}{L_{it}}\right) - \ \ln(L_{it}) = a + \alpha \ln\left(\frac{C_{it}}{L_{it}}\right) + \gamma \ln\left(\frac{K_{it}}{L_{it}}\right) + (\mu - 1) ln\ (L_{it}) + \Sigma\tau_t D_t + \Sigma\sigma_s D_s + \ \epsilon_{it}$$

Where the resulting final variables are:

Dependent Variable:

- $ln\left(\frac{Y}{L}\right)$, the logarithm of Labor Productivity (Sales per employee).

Independent Variables:

- $ln\left(\frac{K}{L}\right)$, Logarithm of R&D Stock per employees (Knowledge Intensity). The coefficient γ measures the elasticity of productivity with respect to innovation.
- $ln\left(\frac{C}{L}\right)$, Logarithm of Physical Capital Stock per employee (Capital Intensity). The coefficient α measures the elasticity of productivity with respect to Capex.
- $\ln(L)$ Logarithm of the Number of Employees (Scale). The coefficient ($\mu - 1$) tests for the presence of returns to scale. If significantly different from zero, it indicates that firm size influences its productivity (non-constant returns to scale).

This specification allows isolating the specific contribution of R&D to productivity, net of physical capital intensity and size effects.

2.4.2 The Pooled OLS Model

Initially, a linear regression model is estimated using Ordinary Least Squares (Pooled OLS), which treats data as if they were a single cross-section, ignoring the panel structure. The model includes a complete set of time dummies (D_t) to capture common macroeconomic shocks (e.g., the 2008 crisis) and sector dummies (D_s) to control for structural heterogeneity across different industries.

2.4.3 The Fixed Effects (FE) model

To address the problem of unobserved heterogeneity (e.g., management quality, corporate culture) that could be correlated with R&D investments, a Fixed Effects model is estimated. This model removes the time-invariant firm-specific component dummies (α_i) through the within transformation (subtracting individual means):

$$(y_{it} - y_i) = \beta_1(k_{it} - k_i) + \beta_2(c_{it} - c_i) + \beta_3(l_{it} - l_i) + \Sigma\tau_t(D_t - D_t) + (\epsilon_{it} - \epsilon_{it})$$

The use of fixed effects is supported by the literature (Hall and Mairesse, 1995) as the preferable method for obtaining consistent estimates of "within-firm" elasticity.

2.4.4 The Random Effect (RE) model

Unlike FE, the Random Effect (RE) model is an estimator that assumes that unobserved differences between observations, in our case firms, are random and unrelated to the variables included in the analysis. This model is more restrictive than the FE one, because it allows for the exploitation of both intra- and inter-enterprise relationships, thus avoiding the introduction of dummies for each firm. The RE model becomes appropriate when the unobserved heterogeneity is assumed to be purely random and not related to the variables considered, in this case Knowledge Capital (R&D) and Physical Capital. In this study, the RE model is estimated in order to apply the Hausman test described below.

2.4.5 Diagnostic tests

Model selection and specification validity are supported by the following statistical tests:

1) Wald Test: used to verify the joint significance of dummies. The test on Time Dummies verifies the presence of significant temporal effects; the test on Sector Dummies (applicable only in POLS) verifies whether sectoral affiliation explains a significant part of productivity variance.
2) Hausman Test: Used to discriminate between the Random Effects (RE) model and the Fixed Effects (FE) model. A significant p-value ($\rho<0.05$) leads to the rejection of the null hypothesis (consistency of RE), indicating that the Fixed Effects model is the appropriate and consistent choice for the analysis.

2.5 Econometric limitations

While the adoption of a Fixed Effects (FE) estimator allows us to control for unobserved time-invariant heterogeneity, thus removing potential bias arising from idiosyncratic characteristics, it does not fully guarantee the identification of a strictly causal relationship between R&D capital and productivity.

A primary concern in the estimation of aggregate production functions is the issue of endogeneity, particularly in the form of simultaneity or reverse causality. Economic theory and empirical evidence suggest that the relationship between innovation and economic performance is likely bidirectional: while R&D investment is expected to enhance future productivity, highly productive economies may also possess greater resources to allocate to R&D activities. Although the Fixed Effects model mitigates omitted variable bias related to time-constant national features, it does not address endogeneity arising from time-varying unobservable or symmetric shocks that affect both input accumulation and output. Furthermore, a specific limitation of the present specification lies in the use of a contemporaneous R&D capital stock variable rather than a lagged specification. Some approaches in the macro-econometric literature adopted, for instance, by Sterlacchini and Venturini (2007; 2014) in their analyses of manufacturing industries consists of introducing R&D capital with a lag structure (specifying lags at t-1 or t-2).

2.6 Limits of the database

At the end of this theoretical framework, it is important to acknowledge an inherent limitation that will inevitably shape the interpretation of the empirical results discussed in the next chapters. The analysis relies on data from the "EU Industrial R&D Investment Scoreboard" a source that, by design, reflects a strong upward selection bias. The dataset includes only the world's largest investors in R&D, representing approximately 90% of global private R&D and, hence, highly representative of the global dynamics of innovative activities. On the other hand, the Scoreboard excludes Small and Medium-sized Enterprises (SMEs) and innovative start-ups that fall below the minimum investment threshold required to be listed (over €67 million to enter the global top 2000 in 2023). This already selective focus is further reinforced by the choice of using a balanced panel. In practice, this means including only firms with complete and continuous data across the entire 2004-2019 and 2009-2019 periods. While this approach ensures statistical consistency, it also restricts the analysis to an even more exclusive group, not just large firms, but those stable and resilient enough to remain active over sixteen years without disruptions such as mergers, acquisitions, or bankruptcies. In other words, the study observes the "top of the top", a consolidated set of long-standing large incumbent companies. This sample homogeneity carries significant statistical implications. By excluding firms that invest less or do so not systematically, the variability within the data is drastically reduced, a phenomenon known as restriction of range. Since econometric analysis depends on variation to uncover causal relationships, it is not surprising that in some sectors or regions the estimated R&D elasticities could be statistically insignificant or smaller in magnitude. Put simply, among firms already at the technological frontier, the marginal return of one additional euro invested in R&D may be less visible than it would be in a more diverse sample that also includes fast-growing, catching-up firms. Therefore, insignificant results should not be interpreted as evidence of a weak or null effect of R&D on productivity.

2.7 Descriptive statistics

As we previously mentioned, our dataset is derived from the EU Industrial R&D Investment Scoreboard and includes firms from our four geographic regions: the United States (US), the European Union (EU), Southeast Asia (SEA), and China. The analysis focuses on the high-tech sectors, in which we have more observations, selected for the econometric estimation: Electronic & Electrical Equipment, Pharmaceuticals & Biotechnology, Software & Computer Services, and Technology Hardware & Equipment. The global country-level dataset[4] is therefore constructed by pooling all firms belonging to the eight sectors, which ensures a consistent sectoral coverage across the different regions.

2.7.1 Sample selection and temporal framework

This section presents the descriptive statistics for the global sample of top R&D investors over the periods 2004-2019 and 2009-2019. The analysis is conducted by comparing two distinct time horizons: the long period (2004-2019), and the post-financial crisis period (2009-2019). These time periods were chosen mainly for two reasons. From an econometric perspective, the 2004-2019 horizon allows us to exploit the longest possible panel, capturing the entire evolution of business R&D and productivity performance in the pre and post-crisis decades. Otherwise, from

[4] Global aggregate sample has been built by all companies present in the main 8 sectors: Automobiles & Parts, Chemicals, Electronic & Electrical Equipment, Health Care Equipment & Services, Industrial Engineering, Pharmaceuticals & Biotechnology, Software & Computer Services, Technology Hardware & Equipment.

an economic point of view, the period 2009-2019 excludes the years of the global financial crisis and COVID-19, focusing on a relatively more stable phase of the business cycle. As we'll analyse in Chapter III, all this allows us to monitor the robustness of the results and to verify whether the elasticities of productivity with respect to R&D are structurally different once the main macroeconomic crises have been neglected from the analysis.

2.7.2 R&D intensity

To assess the innovative propensity of these firms, we analyse the R&D intensity, defined as the ratio of R&D investment to net sales, expressed as a percentage. This indicator reflects the firm's commitment to innovation relative to its output. We report both the simple mean, which averages the R&D intensity across all firms regardless of their size, and the weighted mean (weighted by net sales), which provides an aggregate measure of the R&D intensity of the sector as a whole. The statistics also report the number of firms and the total number of observations (N) available for both periods.

Descriptive analysis 2004-2019

The descriptive statistics of R&D intensity, for the period 2004-2019, are reported in Table 2.1. Looking at the Global Sample, the United States constitutes the largest group with 200 firms and 3,200 observations, followed by Southeast Asia (133 firms) and the European Union (84 firms). China represents a smaller portion of the sample with 22 firms only.

In terms of innovation effort, US firms exhibit the highest simple mean of R&D intensity (10.7%), followed by the EU (7.6%). The Asian regions show significantly lower averages (5.5% for SEA and 6.0% for China). However, when controlling for firm size using the weighted mean, the gap between the two main Western areas narrows almost completely: the US (7.7%) and the EU (7.6%) show practically identical values. This indicates that while the US sample includes a "long tail" of highly intensive smaller firms that push up the simple average, the large European incumbents maintain R&D investment standards comparable to US companies.

Disaggregating the data by high-tech sectors reveals significant heterogeneity across industries and regions. The Pharmaceuticals & Biotechnology sector confirms its role as the primary structural driver of innovation, exhibiting the highest R&D intensity globally. In this industry, both the US and the EU show a remarkable commitment to research, with weighted means of 15.6% and 13.6% respectively, highlighting a substantial parity between the two Western regions. A more marked divergence appears in the Software & Computer Services sector, where the United States displays a clear dominance. US firms not only represent a larger share of the sample (34 firms vs 9 in the EU) but also exhibit a higher weighted R&D intensity (10.4%) compared to their European counterparts (7.0%), suggesting a stronger specialization. Conversely, a different pattern emerges in the hardware-related industries. In Technology Hardware & Equipment, while the US shows a higher simple mean, the European Union reports a superior weighted mean

(13.0% vs 11.2% for the US). A similar trend characterizes the Electronic & Electrical Equipment sector, where the EU weighted mean (5.7%) exceeds that of the US (4.2%). This finding suggests that, although fewer in number, large European incumbents in the manufacturing high-tech sectors maintain a higher R&D propensity relative to the aggregate US sector. Finally, the analysis of the Asian regions highlights a structural gap compared to Western economies. Southeast Asia (SEA) exhibits significantly lower R&D intensities across all sectors, with a global weighted mean of 4.4%. Even in sectors where Asian firms are key global players, such as Technology Hardware, the weighted R&D intensity remains moderate (4.8%). China, while showing a global simple mean of 6.0%, records the lowest global weighted mean (3.7%), suggesting that its R&D activities in this period were still characterized by lower intensity compared to the established Western technology leaders.

Table 2.1 - Descriptive Statistics of R&D Intensity by Region and Sector (2004–2019)

Sector	Metric	Total	US	EU	SEA	China
Global Sample	**Firms**	439	200	84	133	22
	Observations	7,024	3,200	1,344	2,128	352
	Simple Mean (%)	8.3	10.7	7.6	5.5	6.0
	Weighted Mean (%)	6.6	7.7	7.7	4.4	3.7
Electronic & Electrical Equipment	**Firms**	71	28	14	25	-
	Observations	1,136	448	224	400	-
	Simple Mean (%)	7.0	8.0	7.3	5.6	-
	Weighted Mean (%)	4.7	4.2	5.7	5.3	-
Pharmaceuticals & Biotechnology	**Firms**	39	13	11	14	-
	Observations	624	208	176	224	-
	Simple Mean (%)	14.0	17.6	14.2	11.0	-
	Weighted Mean (%)	14.4	15.6	13.6	7.2	-
Software & Computer Services	**Firms**	51	34	9	5	-
	Observations	816	544	144	80	-
	Simple Mean (%)	15.1	16.6	15.9	6.1	-
	Weighted Mean (%)	8.8	10.4	7.0	5.2	-
Technology Hardware & Equipment	**Firms**	75	47	8	15	-
	Observations	1,200	752	128	240	-
	Simple Mean (%)	13.5	16.3	13.2	7.2	-
	Weighted Mean (%)	9.8	11.2	13.0	4.8	-

The sample excludes outliers characterized by R&D Intensity > 100% and specific firms identified as anomalies.

Descriptive analysis 2009-2019

Table 2.2 presents the descriptive statistics for the post-crisis period (2009–2019). Focusing on this timeframe allows for an assessment of R&D strategies during the economic recovery phase.

In terms of geographical distribution, the United States represents the largest group with 256 firms, followed by the European Union (203 firms), Southeast Asia (150 firms) and China with 65 only. Comparing these data with the long-term trends previously discussed three main findings emerge regarding post-crisis investment dynamics.

First, at the aggregate level, while US and EU values were substantially identical in the 2004–2019 period, in the post-2009 decade, the United States exhibits a higher weighted mean intensity (7.7%) compared to the European Union (7.1%). Although the gap remains contained, this signals that the recovery of innovation investments was slightly more dynamic for large US firms compared to their European counterparts. Second, sectoral polarization appears more pronounced. The Software & Computer Services sector sees a consolidation of US leadership, with a weighted mean rising to 11.3% (versus 7.7% for the EU), highlighting the acceleration of the US digital economy during this decade. Conversely, and in continuity with the previous period, Europe confirms a superior performance in Hardware-related industries. In the Technology Hardware sector, specifically, European firms record a weighted mean of 14.6%, a value notably higher than the US figure (10.7%). This confirms that the few remaining large European players in this segment have adopted specialization strategies characterized by extremely high technological intensity. Finally, regarding Asian economies, no significant structural changes are recorded compared to the long-term trend: R&D intensities remain at lower levels relative to Western economies, consistent with the industrial positioning of China and Southeast Asia during the considered decade. Specifically, China records a global weighted mean of 2.7%, while Southeast Asia stands at 4.3%.

Table 2.2 - Descriptive Statistics of R&D Intensity by Region and Sector (2009–2019)

Sector*	Metric	Total	US	EU	SEA	China
Global Sample	**Firms**	674	256	203	150	65
	Observations	7,414	2,816	2,233	1,650	715
	Simple Mean (%)	8.9	12.0	8.4	5.7	6.2
	Weighted Mean (%)	6.4	7.7	7.1	4.3	2.7
Electronic & Electrical Equipment	**Firms**	99	33	28	25	-
	Observations	1,089	363	308	275	-
	Simple Mean (%)	7.6	9.2	7.2	5.4	-
	Weighted Mean (%)	5.2	4.5	6.1	5.2	-
Pharmaceuticals & Biotechnology	**Firms**	70	20	27	14	-
	Observations	770	220	297	154	-
	Simple Mean (%)	13.3	18.7	13.7	11.2	-
	Weighted Mean (%)	14.7	16.2	15.0	7.1	-
Software & Computer Services	**Firms**	89	47	30	6	-
	Observations	979	517	330	66	-
	Simple Mean (%)	15.5	17.1	15.6	5.8	-
	Weighted Mean (%)	8.3	11.3	7.7	2.7	-
Technology Hardware & Equipment	**Firms**	105	57	16	20	-
	Observations	1,155	627	176	220	-
	Simple Mean (%)	14.0	16.7	15.7	8.4	-
	Weighted Mean (%)	8.9	10.7	14.6	5.3	-

The sample excludes outliers characterized by R&D Intensity > 100% and specific firms identified as anomalies.

Chapter III

ECONOMETRIC RESULTS

This chapter presents, respectively, the econometric results relating to US, European, Southeast Asian and Chinese companies. Consistent with the descriptive analysis presented in the previous chapter, the econometric estimation is conducted over two distinct time horizons: the long-term period (2004–2019) and the post-crisis recovery period (2009–2019).

From a methodological point of view, we apply here the models discussed in the previous chapter. We will compare the estimates obtained with the Pooled OLS method with those of the Fixed Effects model. As argued in Chapter II, while the POLS ignores the panel nature of the data by treating each observation as independent, the FE model explicitly controls for time-invariant unobserved heterogeneity (e.g., managerial ability, corporate culture). In this context, the statistical significance of the estimated coefficients is more informative than the overall value of the goodness of fit. In the case of panel FE models, a low R^2 indicates that productivity is driven by external or idiosyncratic factors not captured by annual changes in inputs (R&D capital, Physical Capital); conversely, a high R^2 suggests a highly investment-responsive production process.

As for the coefficient of the logarithm of the number of employees, it does not measure a pure "size effect" on productivity but is used to test returns to scale. A positive and statistically significant coefficient indicates increasing returns to scale, while a negative and significant coefficient indicates decreasing returns to scale. If the coefficient is not significantly different from zero, the data are consistent with constant returns to scale.

It is also important to explain that both capital stocks in the model are divided by the number of employees. R&D capital per employee and physical capital per employee make it possible to isolate the effect of input composition, net of the pure scale effects captured by the employment variable.

The chapter is structured to first analyse the results for each region individually. Subsequently, the final section provides a comparative analysis by region and sector. This cross-regional assessment aims to highlight structural differences in R&D elasticity, identifying which economies and industries exhibit the highest returns on innovation investment and discussing how the technological leadership of the US contrasts with the catching-up dynamics of Asian economies and the heterogeneity of the European context.

3.1 United States

In this section the econometric results of US companies in both timelines (long term 2004-2019 and 2009-2019), are presented by distinguishing between the global aggregate sample and the main industrial sectors selected based on their R&D intensity (see the last section of the previous chapter). Estimates are conducted on the intensive Cobb-Douglas specification described in Chapter II, where the dependent variable is the logarithm of labour productivity and the independent variables are the logs of the knowledge capital stock per employees, the logs of the physical capital stock per employees, while the coefficient of the logarithm of the number of employees, measures the returns to scale.

3.1.1 US long-run analysis

Considering the global US sample, there are a total of 200 top investor companies and 3200 observations.

Looking at Table 3.1, the FE estimation reveals a positive and statistically significant relationship between R&D capital and labour productivity, with an elasticity of approximately 0.288 (Global Sample). This magnitude is considerably higher than that of physical capital (0.129), which is significant only at the 10% level. This confirms that, for the aggregate of top US R&D investors, intangible assets constitute the primary driver of productivity growth.

Regarding the labour coefficient, the value is not significantly different from zero. This result suggests that, at the aggregate level, US firms operate under constant returns to scale, implying that productivity is independent of firm size. The Software & Computer Services sector, supported by a solid sample of 544 observations, confirms the crucial role of innovation. The R&D elasticity is positive and significant (0.362), reflecting the high dependence of digital firms on knowledge capital. The Pharmaceuticals & Biotechnology exhibits the highest responsiveness to innovation, it's highly significant with a substantial R&D elasticity of 0.588. Furthermore, this is the only sector where the labour coefficient is positive and statistically significant (0.201), indicating increasing returns to scale. Finally, in Technology Hardware & Equipment and Electronic & Electrical Equipment the R&D coefficient is not statistically significant. In these relatively mature manufacturing industries, productivity fluctuations appear less driven by within-firm variations in R&D stock and more by physical capital accumulation (which is significant in the Technology Hardware sector) or other unobserved factors. Husman test systematically reject the null hypothesis of consistency of the RE model ($p < 0.05$ for all models), confirming the preferability of FE estimates due to the correlation between unobserved heterogeneity and explanatory variables (see the table notes).

Table 3.1 - United States Global & Sectoral Analysis, 2004-2019

Sector	*Method*	*R&D capital*	*Physical capital*	*Employees*	*Constant*	*R²*	*Obs*
Global Sample	**POLS**	0.318*** (0.029)	0.144*** (0.032)	0.018 (0.020)	-0.260 (0.226)	0.533	3,200
	FE	0.288*** (0.067)	0.129* (0.059)	-0.027 (0.055)	-	0.278	3,200
Electronic & Electrical Equipment	**POLS**	0.300*** (0.072)	0.133 (0.101)	0.047 (0.048)	-0.847** (0.294)	0.558	448
	FE	0.111 (0.077)	0.105 (0.096)	-0.102 (0.070)	-	0.281	448
Pharmaceuticals & Biotechnology	**POLS**	0.848*** (0.241)	-0.212 (0.217)	0.004 (0.022)	-0.385* (0.191)	0.755	208
	FE	0.588*** (0.118)	-0.002 (0.161)	0.201*** (0.056)	-	0.425	208
Software & Computer Services	**POLS**	0.236*** (0.049)	0.254*** (0.047)	-0.033 (0.037)	-0.260 (0.333)	0.553	544
	FE	0.362*** (0.084)	0.085 (0.114)	-0.060 (0.060)	-	0.367	544
Technology Hardware & Equipment	**POLS**	0.402*** (0.049)	0.046 (0.048)	0.041 (0.044)	-0.777* (0.344)	0.487	752
	FE	-0.024 (0.094)	0.266* (0.106)	-0.025 (0.071)	-	0.166	752

*Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1. Wald tests confirm significance of time & sectoral dummies. Hausman's test results (probability of refusing RE): Global (p=0.014), Electronic & Electrical Equipment (p=0.000), Pharmaceuticals & Biotechnology (p=0.000), Software & Computer Services (p=0.015), Technology Hardware & Equipment (p=0.000).*

3.1.2 US post-crisis analysis

In this section, the econometric results of US companies in the post-financial crisis and pre-COVID period 2009–2019 are presented. As shown in Table 3.2, the global sample is composed by 256 enterprises (more firms than those of the previous analysis) giving rise to 2.816 observations.

Compared to the previous analysis, it highlights a big improvement of R&D elasticity at aggregate level, which is highly significant (from 0.288 to 0.451). The sectoral breakdown highlights the dynamic nature of the Software & Computer Services industry, where the R&D elasticity increases to 0.411, up from 0.362 in the long run, indicating an intensified dependence on knowledge capital. Structural stability characterizes Pharmaceuticals & Biotechnology, where the R&D coefficient remains highly significant and robust at 0.529, comparable to the long-term value. It confirms an increasing return to scale (with a labour coefficient of 0.230).

A change is observed in Technology Hardware: unlike the long-run results where innovation was not significant, the post-crisis R&D coefficient becomes positive (0.338), albeit only weakly significant at the 10% level. Conversely, Electronic & Electrical Equipment follows the long-term trend, as R&D remains statistically insignificant and productivity appears driven entirely by physical capital accumulation (0.424). The diagnostic tests support the specifications choices (see the table notes)

Table 3.2 - United States Global & Sectoral Analysis, 2009-2019

Sector	Method	R&D capital	Physical capital	Employees	Constant	R²	Obs
Global Sample	**POLS**	0.313*** (0.030)	0.182*** (0.030)	0.033 (0.021)	-0.382 (0.233)	0.559	2,816
	FE	0.451*** (0.079)	0.138* (0.054)	0.063 (0.059)	-	0.331	2,816
Electronic & Electrical Equipments	**POLS**	0.382*** (0.075)	0.151* (0.061)	0.056 (0.051)	-0.729* (0.319)	0.713	363
	FE	0.243 (0.157)	0.424*** (0.104)	0.177 (0.138)	-	0.393	363
Pharmaceutcals & Biotechnology	**POLS**	0.501*** (0.114)	0.026 (0.078)	-0.028 (0.025)	-0.085 (0.298)	0.578	220
	FE	0.529*** (0.131)	-0.021 (0.068)	0.230*** (0.049)	-	0.267	220
Software & Computer Services	**POLS**	0.328*** (0.058)	0.179*** (0.039)	-0.003 (0.029)	-0.425 (0.283)	0.554	517
	FE	0.411*** (0.098)	0.053 (0.063)	0.023 (0.082)	-	0.263	517
Technology Hardware & Equipments	**POLS**	0.368*** (0.054)	0.186* (0.073)	0.038 (0.044)	-0.622 (0.369)	0.475	627
	FE	0.338* (0.169)	0.239* (0.105)	0.111 (0.096)	-	0.196	627

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Wald tests confirm significance of time & sectoral dummies. Hausman's test result (probability of refusing RE): Global (p=0.081), Electronic & Electrical Equipment (p=0.005), Pharmaceuticals & Biotechnology (p=0.003), Software & Computer Services (p=0.015), Technology Hardware & Equipment (p=0.192).*

3.2 Europe

As in the US analysis, this section presents the econometric results of European Union companies, also considering British companies before the Brexit, in the two-time horizon: 2004–2019 and 2009-2019.

Unlike the relatively homogeneous US market, the European context is characterized by structural heterogeneity arising from linguistic barriers, institutional diversity, and geographical fragmentation. Despite this complexity, the analysis focuses on the global aggregate and industrial sectors with high R&D intensity. We have chosen to consider the same sectors used for the US analysis.

3.2.1 Europe long-run analysis

Compared to the US case, the European dataset for the period 2009-2019, includes fewer enterprises (84) giving rise to 1344 observations.

As can be seen from Table 3.3, at the Global level, the Fixed Effects estimation does not yield a statistically robust coefficient for R&D. Therefore, we cannot confirm a significant link between within-firm R&D accumulation and productivity growth for the aggregate European sample in this period. At sectoral level, Technology Hardware & Equipment emerges as the top-performing sector in Europe. The R&D elasticity is remarkably high (0.896) and statistically significant. However, given the limited number of firms in this subsample, this magnitude should be interpreted with caution. Software & Computer Services also shows a positive and significant link between innovation and productivity, with an R&D

elasticity of 0.201. This value suggests a solid contribution of innovation to productivity.

The Pharmaceuticals & Biotechnology sector presents a surprising result compared to the US. While the POLS estimate shows a significant R&D coefficient (0.303), the significance vanishes in the FE specification (0.000). This implies that productivity differences are driven by structural, time-invariant firm characteristics (cross-sectional dimension) rather than by annual variations in R&D stock. Electronic & Electrical Equipment sector the R&D coefficient is not significant. However, this sector is characterized by a strongly negative labour coefficient (-0.345), pointing to significant decreasing returns to scale. Finally, the Wald tests confirm the joint significance of time dummies across all specifications, validating the need to control for common macroeconomic shocks affecting the Eurozone economy.

Table 3.3 - Europe Global & Sectoral Analysis, 2004-2019

Sector	Method	R&D capital	Physical capital	Employees	Constant	R²	Obs
Global Sample	**POLS**	0.101 (0.055)	0.216 (0.111)	-0.006 (0.026)	-0.767** (0.274)	0.407	1,344
	FE	0.203* (0.080)	0.032 (0.105)	-0.214** (0.074)	-	0.378	1,344
Electronic & Electrical Equipments	**POLS**	0.168 (0.139)	-0.016 (0.095)	-0.036 (0.068)	-0.953 (0.550)	0.253	224
	FE	0.017 (0.082)	0.070 (0.107)	-0.345*** (0.093)	-	0.47	224
Pharmaceutical & Biotechnology	**POLS**	0.303*** (0.090)	-0.356** (0.106)	0.056 (0.046)	-2.034*** (0.467)	0.326	176
	FE	0.000 (0.183)	-0.613 (0.328)	-0.389 (0.284)	-	0.351	176
Software & Computer services	**POLS**	0.421*** (0.087)	-0.126* (0.060)	0.143*** (0.040)	-2.196*** (0.163)	0.761	144
	FE	0.201*** (0.051)	-0.071 (0.106)	-0.121 (0.087)	-	0.741	144
Technology & Hardware Equipment	**POLS**	0.447*** (0.132)	0.090 (0.178)	0.044 (0.049)	-0.588 (0.620)	0.510	128
	FE	0.896*** (0.210)	0.084 (0.199)	0.128 (0.188)	-	0.578	128

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Wald tests confirm significance of time & sectoral dummies. Hausman's test results (probability of refusing RE): Global (p=0.000), Electronic & Electrical Equipment (p=0.003), Pharmaceuticals & Biotechnology (p=0.008), Software & Computer Services (p=0.000), Technology Hardware & Equipment (p=0.186).*

3.2.2 Europe post-crisis analysis

Table 3.4 presents the econometric results of European and British companies in the post-financial crisis and pre-COVID period 2009–2019.

Compared to the previous period of analysis, the European dataset includes much more enterprises, 203 giving rise to 2233 observations, although always fewer than US. At the Global level, the FE estimation indicates a positive R&D elasticity (0.183), significant at the 5% level. Physical capital and labour coefficient are not statistically significant. At sectoral level, Software & Computer Services consolidates the positive trajectory (R&D capital is significant 0.200), confirming the role of knowledge capital for digital firms in the recovery period. Pharmaceuticals & Biotechnology remains capital-intensive (R&D capital not significant -0.663, Physical Capital 0.819). In this period, Technology Hardware & Equipment exhibits a not statistically significant coefficient (unlike the long-run result), suggesting that within-firm variations in R&D did not significantly drive productivity changes in this specific timeframe. Finally, for Electronic & Electrical Equipment's, neither R&D nor labour coefficients are significant. Hausman specification test rejects RE in favour of FE across all models ($p < 0.05$), confirming the presence of unobserved heterogeneity correlated with regressors. The results are reported in the table notes.

Table 3.4 - Europe Global & Sectoral Analysis, 2009-2019

Sector	Method	R&D capital	Physical capital	Employees	Constant	R^2	Obs
Global Sample	**POLS**	0.212*** (0.034)	0.179*** (0.045)	-0.005 (0.013)	-0.478** (0.169)	0.541	2,233
	FE	0.183** (0.069)	0.153* (0.063)	-0.075 (0.051)	-	0.272	2,233
Electronic & Electrical Equipments	**POLS**	0.315** (0.110)	-0.039 (0.087)	-0.033 (0.047)	-0.747 (0.390)	0.401	308
	FE	0.037 (0.135)	0.157* (0.079)	-0.227 (0.117)	-	0.353	308
Pharmaceutucal & Biotechnology	**POLS**	0.355*** (0.060)	-0.053 (0.155)	0.018 (0.024)	-0.980* (0.388)	0.554	297
	FE	-0.037 (0.181)	0.203 (0.281)	0.053 (0.259)	-	0.128	297
Software & Computer Services	**POLS**	0.230** (0.076)	0.016 (0.060)	0.013 (0.045)	-1.393*** (0.342)	0.318	330
	FE	0.200** (0.067)	0.054 (0.050)	-0.011 (0.089)	-	0.431	330
Technology & Hardware Equipments	**POLS**	0.480*** (0.113)	0.235*** (0.070)	-0.011 (0.029)	-0.070 (0.368)	0.602	176
	FE	0.171 (0.284)	0.193 (0.116)	0.037 (0.130)	-	0.199	176

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Wald tests confirm significance of time & sectoral dummies. Hausman's test results (probability of refusing RE): Global (p=0.000), Electronic & Electrical Equipment (p=0.005), Pharmaceuticals & Biotechnology (p=0.000), Software & Computer Services (p=0.519), Technology Hardware & Equipment (p=0.035).*

3.3 Asia

This section examines Asia's high-tech economies, considering Japan, Taiwan, Singapore, South Korea, and China. Observations from Japan, Taiwan, Singapore, and South Korea are analysed as a single population under the name "Southeast Asia". Differently, China has been analysed individually.

3.3.1 Southeast Asia

This section extends the analysis to the leading Asian high-tech economies, specifically Japan, South Korea, Taiwan, and Singapore. Consistent with the methodology applied to the US and the EU, we present the econometric results for two distinct time horizons: 2004–2019 and 2009–2019. To ensure comparability with the previous analyses, the study focuses on the same four R&D-intensive sectors, which also represent the most populated industries within the Asian dataset.

Long-run analysis

This subsection analyses the long-term link between R&D intensity and labour productivity for enterprises in South-East Asia. Due to limited information availability in the 2004–2019 period, the long-term sample includes exclusively Japanese and Taiwanese firms, while South Korean and Singaporean firms are present only in the post-crisis analysis. The dataset comprises 133 firms, generating a total of 2,128 observations.

As can be seen from Table 3.5, at the Global level, the Fixed Effects model yields no statistically significant coefficients for R&D or physical capital. The only robust evidence concerns the labour coefficient, which is negative and significant (-0.304), indicating that the average Southeast Asian firm operates under decreasing returns to scale. The sectoral breakdown identifies Technology Hardware & Equipment as the primary driver of innovation-led productivity in the region. This is the only sector exhibiting a positive and highly significant R&D elasticity (0.616). Conversely, results for Software & Computer Services must be interpreted with caution due to the limited sample (only 80 observations); here, productivity appears driven by physical capital (0.744) rather than intangible assets. Finally, Electronic & Electrical Equipment confirms the aggregate trend of decreasing returns to scale (-0.414), with no significant contribution from R&D investment.

Table 3.5 - Southeast Asian Countries Global & Sectoral analysis, 2004-2019

Sector	Method	R&D capital	Physical capital	Employees	Constant	R²	Obs
Global Sample	**POLS**	0.258*** (0.074)	0.203* (0.081)	-0.073* (0.034)	0.406 (0.485)	0.527	2128
	FE	0.219* (0.109)	0.189* (0.074)	-0.304** (0.094)	-	0.501	2128
Electronic & Electrical Equipments	**POLS**	0.546*** (0.119)	-0.029 (0.107)	-0.109 (0.059)	0.812 (0.595)	0.69	400
	FE	0.229 (0.172)	-0.041 (0.074)	-0.414** (0.150)	-	0.587	400
Pharmaceutical & Biotechnology	**POLS**	-0.168 (0.106)	0.093 (0.164)	0.164** (0.063)	-2.741*** (0.609)	0.314	224
	FE	0.335 (0.394)	0.154 (0.248)	0.093 (0.170)	-	0.271	224
Software & Computers Services	**POLS**	-0.132** (0.047)	0.531*** (0.047)	-0.126*** (0.021)	0.626** (0.182)	0.779	80
	FE	-0.133*** (0.020)	0.744*** (0.030)	-0.249*** (0.024)	-	0.902	80
Technology & Hardware Equipments	**POLS**	0.203 (0.202)	0.422* (0.180)	-0.177 (0.105)	1.346 (0.743)	0.475	240
	FE	0.616*** (0.103)	0.080 (0.135)	-0.076 (0.081)	-	0.673	240

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Wald tests confirm significance of time & sectoral dummies. Hausman's test results (probability of refusing RE): Global (p=0.024), Electronic & Electrical Equipment (p=0.362), Pharmaceuticals & Biotechnology (p=0.000), Software & Computer Services (p=0.000), Technology Hardware & Equipment (p=0.337).*

Post-crisis analysis

Compared to the long-run analysis, this narrower time horizon presents fewer observations but greater geographic coverage, including firms from Japan, South Korea, Taiwan, and Singapore. The dataset comprises 155 firms, generating a total of 1650 observations.

As we can see from Table 3.6, at the Global level, the Fixed Effects estimation reveals that the link between capital inputs and productivity is not statistically robust in the aggregate sample. As in the previous analysis, neither R&D capital nor physical capital coefficients reach the 5% significance threshold. For the sectoral analysis, Pharmaceutical & Biotechnology sector exhibits a remarkably high and significant responsiveness to innovation, with an R&D elasticity of 0.981. Similarly, the Technology & Hardware Equipment sector confirms its strategic role in the region, showing a positive and highly significant R&D coefficient (0.782). In this specific sector, physical capital presents a negative and significant coefficient (-0.275), suggesting a potential substitution effect or over-capitalization issues in tangible assets during this period. Conversely, the Electronic & Electrical Equipment sector shows no statistically significant coefficients. Finally, results for Software & Computer Services do not yield any significant estimates in the Fixed Effects model; however, this lack of robustness must be attributed to the extremely small sample size (only 66 observations), which prevents reliable econometric inference.

Table 3.6 - Southeast Asian Countries Global & Sectoral analysis, 2009-2019

Sector	Method	R&D capital	Physical capital	Emplyoees	Constant	R²	Obs
Global Sample	**POLS**	0.204** (0.068)	0.269*** (0.067)	-0.054 (0.029)	0.051 (0.388)	0.559	1650
	FE	0.141* (0.063)	0.092 (0.049)	-0.448*** (0.085)	-	0.489	1650
Electronic & Electrical Equipments	**POLS**	0.466*** (0.110)	0.094 (0.118)	-0.066 (0.061)	0.316 (0.646)	0.638	275
	FE	0.268 (0.228)	0.352 (0.182)	0.024 (0.222)	-	0.582	275
Pharmaceutical & Biotechnology	**POLS**	-0.134 (0.109)	0.217 (0.140)	0.168* (0.070)	-2.386** (0.717)	0.291	154
	FE	0.981*** (0.159)	-0.126 (0.092)	-0.121* (0.054)	-	0.592	154
Software & Computer Services	**POLS**	-0.090* (0.044)	0.503*** (0.053)	-0.029 (0.015)	-0.381 (0.245)	0.944	66
	FE	-0.123 (0.080)	0.635 (0.403)	0.275 (0.262)	-	0.278	66
Technology & Hardware Equipments	**POLS**	0.295* (0.137)	0.277* (0.140)	-0.149* (0.067)	1.069 (0.622)	0.512	220
	FE	0.782*** (0.139)	-0.275** (0.083)	-0.066 (0.152)	-	0.431	220

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Wald tests confirm significance of time & sectoral dummies. Hausman's test results (probability of refusing RE): Global (p=0.000), Electronic & Electrical Equipment (p=0.000), Pharmaceuticals & Biotechnology (p=0.000), Software & Computer Services (p=0.030), Technology Hardware & Equipment (p=0.000).*

3.3.2 China

In contrast to previous sections, this analysis presents the econometric results for Chinese firms over the 2004–2019 and 2009–2019 periods. Given the significantly smaller sample size relative to other regions, a sectoral disaggregation was not feasible. Therefore, to ensure statistical robustness, the analysis is restricted to the aggregate level.

Long-run analysis

The Table 3.7 presents the estimated coefficients for the full sample available over the period 2004–2019. The Chinese dataset comprises 22 investing companies, resulting in a total of 352 observations. Given the limited sample size, the results should be interpreted with caution, as they may lack statistical robustness.

At the aggregate level, FE estimation reveals a remarkably strong and statistically significant relationship between innovation and productivity. The elasticity of R&D capital stands at 0.496, indicating that for this select group of Chinese listed companies, intangible assets are the primary engine of growth. In contrast, the coefficient for physical capital does not reach the 5% significance threshold in the FE specification. A distinctive feature of the Chinese sample concerns the labor coefficient, which is positive and highly significant (0.325). This provides robust evidence of increasing returns to scale, suggesting that these firms benefit substantially from size expansion and market consolidation.

Table 3.7 - China Global analysis, 2004-2019

Sector	Method	R&D capital	Physical capital	Employees	Constant	R²	Obs
Global Sample	**POLS**	0.591** (0.210)	0.001 (0.173)	0.225 (0.116)	-2.125* (1.018)	0.495	352
	FE	0.496*** (0.096)	0.328 (0.167)	0.325*** (0.091)	-	0.539	352

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Hausman's test results: Global (0.183).*

Post-crisis analysis

In this section, the estimated coefficients are reported for the full sample available in the period 2009-2019, with 65 investing companies, for a total of 715 observations, few more observations than the long-run analysis (2009-2019).

As we can see from Table 3.8 at the aggregate level, estimation results confirm the central role of intangible assets in driving productivity for Chinese firms. The elasticity of R&D capital is positive and highly significant (0.423), demonstrating a robust return on innovation investment during the recovery phase. In contrast, the coefficient for physical capital is not significant. Regarding returns to scale, the labour coefficient is not statistically significant (0.016), indicating that in the post-2009 period, the Chinese sample operates under constant returns to scale, suggesting a normalization of growth dynamics compared to the increasing returns observed in the longer timeframe.

Table 3.8 - China Global analysis, 2009-2019

Sector	Method	R&D capital	Physical capital	Employees	Constant	R^2	Obs
Global Sample	**POLS**	0.453*** (0.092)	0.217*** (0.060)	0.234** (0.072)	-1.808** (0.584)	0.446	715
	FE	0.423*** (0.111)	0.163* (0.079)	0.016 (0.076)	Included -	0.317	715

*Statistical significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Hausman's test results: Global (0.005).*

3.4 Comparative analysis

This section performs a comparative analysis of the elasticity of R&D capital on labour productivity across the four geographic areas under study. The objective is to stress heterogeneities in the returns to innovation, both at the aggregate national level and across specific industrial sectors. The econometric estimation maintains the Fixed Effects (FE) specification adopted in the previous sections, controlling for firm-specific time-invariant characteristics and common macroeconomic shocks.

3.4.1 Comparative analysis across countries

This section presents aggregate estimates of the R&D capital elasticity on labour productivity at the country level. The analysis compares the results obtained for the United States, the European Union, Southeast Asia, and China across two timeframes: the long-term period (2004–2019) and the post-crisis period (2009–

2019). Table 3.9 compares the R&D coefficients for the four regions over the two periods.

Table 3.9 - Comparative analysis of R&D elasticities across countries

	Long-run 2004-2019				Post crisis 2009-2019			
Country	**R&D**	**R^2**	**Obs**	**Firms**	**R&D**	**R^2**	**Obs**	**Firms**
US	0.288***	0.278	3,200	200	0.451***	0.331	2,816	256
EU	0.203*	0.378	1,344	84	0.183**	0.272	2,233	203
SEA	0.219*	0.501	2,128	133	0.141*	0.489	1,650	150
China	0.496***	0.539	352	22	0.423***	0.317	715	65

The global sample includes varying numbers of firms, with the US representing the largest group (200 firms). The econometric results reveal a clear divergence in the returns to innovation between Western and Asian economies. In the long-run analysis (2004–2019), the United States exhibits a positive and highly significant R&D elasticity (0.288). This result, supported by the largest number of observations (3,200), confirms that for top US investors, R&D stock is a structural driver of productivity growth. China records the highest elasticity in the sample (0.496), which is statistically significant; however, this magnitude must be interpreted with caution due to the limited sample size (only 22 firms) available for this period, which may reflect the performance of a few highly dynamic champions rather than the entire economy.

Conversely, the results for the European Union and Southeast Asia show lower R&D elasticities with a low level of statistical significance; suggesting that over the long run, the link between within-firm R&D accumulation and productivity growth was less strong in these regions compared to the US.

Moving to the post-crisis period (2009–2019), US companies show a remarkable strengthening of the innovation-productivity link, with the R&D elasticity rising to 0.451 while remaining highly significant. A notable change is observed for the European Union: in this recovery phase, supported by the larger sample (from 84 to 203), the R&D elasticity becomes statistically significant, but its magnitude remains lower than that of the US. Regarding Asian economies, China confirms its high responsiveness to R&D with a significant coefficient of 0.423, based on an increased sample size (65 firms). Southeast Asia, however, continues to show no significant relationship between R&D stock and productivity.

3.4.2 Comparative analysis across sectors 2004-2019

Table 3.10 presents the comparative analysis of R&D elasticities across sectors for the United States, the European Union, and Southeast Asia over the period 2004–2019. China is excluded from this sectoral breakdown due to the insufficient number of observations in specific industries, which prevents reliable econometric inference.

Table 3.10 - Comparative analysis of R&D elasticities across sectors (2004-2019)

Sectors	**US**	**EU**	**SEA**
Electronic & Electrical Equipment			
R&D	0.111	0.017	0.229
R^2	0.281	0.47	0.587
Obs	448	224	400
Firms	28	14	25
Pharmaceutical & Biotechnology			
R&D	0.588***	0.000	0.335
R^2	0.425	0.351	0.271
Obs	208	176	224
Firms	13	11	14
Software & Computer Services			
R&D	0.362***	0.201***	-0.133***
R^2	0.367	0.741	0.902
Obs	544	144	80
Firms	34	9	5
Technology & Hardware Equipment			
R&D	-0.024	0.896***	0.616***
R^2	0.166	0.578	0.673
Obs	752	128	240
Firms	47	8	15

The analysis reveals a stark dichotomy in regional specialization. The United States asserts its dominance in intangible-intensive and science-based sectors. Specifically, in Pharmaceuticals & Biotechnology, the US is the only region exhibiting a positive and highly significant R&D elasticity (0.588). In contrast, estimates for the EU and SEA in this sector are not statistically significant in the Fixed Effects specification, suggesting that the structural link between innovation stock and productivity in the pharmaceutical industry is a unique characteristic of the US sample.

A similar pattern is observed in Software & Computer Services, which emerges as the only sector yielding statistically significant coefficients across all three regions, albeit with divergent implications. The US leads with a robust elasticity of 0.362, supported by the largest sample size (544 observations). The EU follows with a positive and significant coefficient (0.201). Conversely, Southeast Asia presents a significant but negative coefficient (-0.133); however, this result must be interpreted with caution given the small sample size (only 80 observations), suggesting that for these specific Asian firms, productivity was driven by factors other than intangible accumulation.

The scenario reverses when analysing the Technology & Hardware Equipment sector. Here, the United States shows no significant return on R&D. Instead, the European Union records its highest sectoral elasticity (0.896), followed closely by Southeast Asia (0.616). This highlights a clear specialization: while US productivity is driven by software and biotech, European and Southeast Asian firms maintain a competitive edge and strong returns to innovation in the high-tech manufacturing hardware supply chain. Finally, the Electronic & Electrical Equipment sector shows no statistically significant R&D elasticities across any of the three regions, indicating a uniform lack of responsiveness to within-firm R&D variations in this relatively mature industry.

3.4.3 Comparative analysis across sectors 2009-2019

Table 3.11 displays the comparative results for the post-crisis period (2009–2019). Like the long-run analysis, China is excluded due to insufficient observations for sectoral disaggregation. The Pharmaceutical & Biotechnology sector exhibits a polarized landscape. The United States confirms its leadership in science-based industries with a high and statistically significant R&D elasticity (0.529). Notably, Southeast Asia records an even higher coefficient (0.981). However, this result should be interpreted with caution given the small sample size (14 companies). While it suggests that R&D investment yielded exceptional returns during the recovery phase, the limited number of firms prevents robust generalizations. In contrast, the European Union shows no significant link between innovation and productivity in this sector.

In Software & Computer Services, United States leads with a robust coefficient of 0.411, followed by the European Union, which maintains a positive and significant elasticity (0.200). This confirms that the digital economy was a primary driver of productivity growth for Western economies after the crisis. Conversely, results for Southeast Asia are not statistically significant; however, this must be attributed to the extremely small sample size (only 6 firms), which prevents any reliable econometric inference.

Finally, the Technology & Hardware Equipment sector highlights the specific competitive advantage of Southeast Asia. This is the only region where R&D elasticity is positive and highly significant (0.782). In contrast, although the US shows a positive coefficient (0.338), it is significant at the 10% level only. The Electronic & Electrical Equipment sector confirms the trend observed in the long run, with no statistically significant coefficients found across any of the three regions.

Table 3.11 - Comparative analysis of R&D elasticities across sectors (2009-2019)

Sectors	US	EU	SEA
Electronic & Electrical Equipment			
R&D	0.243	0.037	0.268
R^2	0.393	0.353	0.582
Obs	363	308	275
Firms	33	28	25
Pharmaceutical & Biotechnology			
R&D	0.529***	-0.037	0.981***
R^2	0.267	0.128	0.592
Obs	220	297	154
Firms	20	27	14
Software & Computer Services			
R&D	0.411***	0.200***	-0.123
R^2	0.263	0.431	0.278
Obs	517	330	66
Firms	47	30	6
Technology & Hardware Equipments			
R&D	0.338*	0.171	0.782***
R^2	0.285	0.199	0.431
Obs	627	176	220
Firms	57	16	20

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Concluding remarks

The present thesis has investigated the relationship between R&D investment and firm productivity across four distinct geographical areas: United States, European Union, Southeast Asia, and China over the period 2004–2019, with a specific focus on the post-crisis recovery. This was done by estimating an augmented production function using Fixed Effects models on a sample of top global R&D investors. Although the Fixed Effects estimators mitigate bias arising from time-invariant heterogeneity, it does not fully address endogeneity issues.

The econometric evidence reveals a clear hierarchy in the efficiency of R&D investments, characterized by a marked divergence. The United States stands out as the global technological leader, exhibiting the highest and most robust R&D elasticity throughout the entire period. This structural advantage notably strengthened in the post-crisis years, suggesting that US firms successfully leveraged intangible assets to drive their recovery. In contrast, the European Union presents two different situations: while long-run estimates do not show a statistically robust link between R&D and productivity, the post-crisis period marks a turning point. After 2009, European firms demonstrated a significant positive response to innovation, indicating a successful restructuring of their investment strategies, although the magnitude of these returns remains lower than that of their US counterparts.

Beyond aggregate trends, the analysis uncovers a distinct pattern of sectoral specialization that defines the competitive advantage of each region. The US dominance is driven primarily by science-based and digital industries, specifically Pharmaceuticals & Biotechnology and Software & Computer Services, where US firms show a unique ability to translate research into productivity. Conversely, Europe and Southeast Asia find their competitive edge in Technology & Hardware Equipment. Southeast Asia displays its strength on that, which stands as the only sector in the region with robust returns to R&D, while other industries do not show significant responsiveness to innovation inputs. Regarding China, the analysis identifies high elasticity values typical of a "catching up" economy, accompanied by a transition from increasing to constant returns to scale in the post-crisis period. These empirical findings find theoretical support in the established literature, confirming that the relationship between R&D and productivity is structurally dependent on sectoral composition and the stage of economic development.

First, the persistent gap between the United States and the European Union corroborates the "structural burden" hypothesis advanced by Ortega-Argilés, Piva, and Vivarelli (2015). The results show that the US advantage is not quantitative but qualitative, driven by a concentration of firms in high-tech sectors (Software & Computer Services and Pharmaceuticals & Biotechnology) characterized by higher R&D elasticities. Conversely, the lower responsiveness of European firms aligns with their conclusion that the EU's industrial structure, still heavily reliant on medium-tech manufacturing, naturally yields lower marginal returns on innovation compared to the science-based US ecosystem.

Second, the remarkable performance of the US in the Software & Computer Services sector offers empirical validation to the insights of Lotti, Hall, and Mairesse (2013) regarding the pivotal role of ICT. The high and robust elasticity observed for US firms in this sector confirms that the "digital revolution" remains the primary engine of productivity growth in advanced economies. It suggests that US firms possess a superior capability to combine R&D investments with intangible assets, generating a complementarity effect that is less evident in other regions.

Third, the lack of statistical significance found in the European Pharmaceutical & Biotechnology sector reflects the structural challenges identified by Schuhmacher et al. (2023). This finding highlights a potential productivity crisis within the industry, often referred to as "Eroom's Law," where the cost of developing new drugs increases exponentially while the marginal return on R&D diminishes. The econometric evidence suggests that for European incumbents, massive R&D spending is no longer translating into productivity gains, signalling a saturation in traditional innovation models.

Finally, the trajectory of China provides a clear illustration of the dynamics described by Montresor and Vezzani (2015). The exceptionally high elasticity observed is typical of "top R&D investors" operating in a catch-up phase, benefiting from the adoption of existing technologies.

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