



UNIVERSITÀ
DI PAVIA

DEPARTMENT OF ECONOMICS AND
MANAGEMENT

Master's Program in Economics, Development, and Innovation

Curriculum Industrial Organization and Innovation

**Patents, Standards, and Patterns of
Innovation.
Evidence from the Development of
Wi-Fi Technology**

Supervisor: Prof. Roberto Fontana

Written by: Sofi Hasalliu

Number: 542184

Academic Year 2024-2025

ABSTRACT

This thesis analyzes the relationship between technological standardization and innovation through the case of Wi-Fi, one of the most representative technologies in the contemporary digital economy. The purpose is to understand how the standardization process influences the innovation activity, the competitive strategies, and the technological performance of firms over time.

The analysis combines patent data and econometric methodologies to evaluate the impact of Wi-Fi standardization on the dynamics of innovation. A dataset of more than 60,000 Wi-Fi-related patents (1924-2020) was able to explore the evolution of patenting activity, technological specialization, and firm behavior within the IEEE 802.11 family of standards. Descriptive statistics show a strong increase in patenting after the introduction of the standard, while econometric models, based on count data, panel regressions, and survival analysis, show that participation in standardization is associated with higher innovative output and longer firm survival.

Results highlight the strategic role of essential patents (Standard-Essential Patents, SEP) in balancing competition and cooperation among firms. Standardization acted both as an engine of diffusion and as a mechanism of coordination, which contributed to defining the structure of the Wi-Fi ecosystem.

Overall, the thesis contributes to the literature on the economics of innovation and standardization, demonstrating how open standardization, when supported by transparent governance and FRAND licensing standardization, can promote collective innovation and technological progress.

TABLE OF CONTENTS

<i>LIST OF TABLES</i>	1
<i>LIST OF FIGURES</i>	2
<i>INTRODUCTION</i>	3
<i>CHAPTER 1</i>	5
<i>LITERATURE REVIEW</i>	5
1.1 Chapter Introduction	5
1.2 Patents as Instruments of Innovation Appropriation.....	6
1.2.1 Theoretical Approaches	6
1.2.2 Empirical Evidence	8
1.3 Patents as Economic Indicators of Innovation.....	9
1.3.1 The use of patents as a proxy for innovative activity.....	9
1.3.2 Relationship between R&D and patenting output.....	11
1.3.3 Patent Citations and Economic Value.....	13
1.4 Patents as Strategic Assets and Tools of Competition	14
1.4.1 Patents, Firm Strategy, and Technological Markets.....	14
1.4.2 Patent Thickets and Defensive Patenting.....	15
1.4.3 Patents and the Structure of Technological Markets.....	17
1.5 Technological Standards, Innovation, and Patents	18
1.5.1 The Economics of Technological Standards	18
1.5.2 Patents and Standardization Processes.....	19
1.5.3 Innovation Dynamics in ICT Industries.....	20
1.6 Chapter Conclusions	22
<i>CHAPTER 2</i>	24
<i>CONTEXT OF ANALYSIS: THE Wi-Fi INDUSTRY</i>	24
2.1 Chapter Introduction	24
2.2 The Regulatory Roots of Wi-Fi.....	25
2.3 The IEEE 802.11 standard	27
2.4 Market Dynamics and Wi-Fi Adoption.....	29
2.5 Winners and Losers of Standardization	31
2.6 Economic and Policy Implications	33
2.7 Conclusion	33
<i>CHAPTER 3</i>	35
<i>DATASET AND DESCRIPTIVE STATISTICS</i>	35
3.1 Dataset Description.....	35
3.2 Data Cleaning and Variable Construction.....	37
3.3 Descriptive Statistics.....	39
3.3.1 Patent Activity Over Time	39
3.3.2 Patent Technological Distribution (IPC).....	41

3.3.3 Entry – Exit Dynamics of Firms.....	44
3.3.4 Patent Concentration	46
3.3.5 Ranking Over Time.....	48
3.3.6 Citations and Innovative Impact.....	51
3.3.7 Summary and conclusions of the descriptive analysis	54
CHAPTER 4 ECONOMETRIC ANALYSIS.....	56
4.1 Introduction.....	56
4.2 Datasets and Variables	57
4.3 Econometric Method	58
4.3.1 Count Data Models.....	58
4.3.2 Panel Regressions	59
4.3.3 Survival Models.....	60
4.4 Results: Count Data Models.....	63
4.4.1 Diagnostics: over-dispersion and robust inference	63
4.4.2 Determinants of Patent Number	64
4.4.3 Determinants of Patent Quality	70
4.5 Results: Panel Regressions	75
4.5.1 Robustness Checks	77
4.6 Results: Survival Analysis	78
4.6.1 Non-parametric analysis	79
4.6.2 Cox Proportional Hazards	81
4.6.3 Robustness Checks	82
4.6.4 Discussion of Survival Analysis.....	85
4.7 Conclusion	86
CONCLUSIONS.....	88
BIBLIOGRAPHY	90
APPENDIX.....	93

LIST OF TABLES

Table 3.1 – Number of Patents by Period, p. 40

Table 3.2 – Average of Number of IPC Classes by Period, p. 42

Table 3.3 – Number of Patents by Main IPC Class, p. 43

Table 3.4 – HHI Over Time, p. 46

Table 3.5 CR4 Over Time, p. 48

Table 3.6 – Top 10 Firm Ranking by Period, p. 49

Table 3.7 – Distribution of Cited Patents Over Time, p. 53

Table 3.8 – Distribution of Citing Patents Over Time, p. 53

Table 4.1 – Poisson Regressions for Patent Counts (Dependent variable: annual rate of Wi-Fi patents; IRRs reported), p. 65

Table 4.2 – Negative Binomial Regressions for Patent Counts (Dependent variable: annual rate of Wi-Fi patents; IRRs reported), p.68

Table 4.3 – Poisson Regressions for Forward Citations (Dependent variable: annual rate of forward citations; IRRs reported), p. 71

Table 4.4 – Negative Binomial Regressions for Forward Citations (Dependent variable: annual rate of forward citations; IRRs reported), p. 73

Table 4.5 – Panel Regressions of Revenues on Patenting Activity, p. 76

Table 4.6 – Cox Proportional Hazards Regression Results (Dependent variable: firm exit), p. 82

Table 4.7 – Weibull Proportional Hazards Regression Results (Dependent variable: firm exit), p. 83

Table 4.8 – Discrete-time Cloglog Regression Results (Dependent variable: firm exit), p. 85

LIST OF FIGURES

- Figure 3.1* – Evolution of Wi-Fi Patents Over Time (1924 – 2020), p. 41
- Figure 3.2* – Distribution of Average Number of IPC Classes by Period, p. 42
- Figure 3.3* – Entry and Exit of Firms in the Patent Market, p. 44
- Figure 3.4* – Company Life Duration, p. 45
- Figure 3.5* – Distribution of HHI Over Time, p. 47
- Figure 3.6* – Distribution of CR4 Over Time, p. 48
- Figure 3.7* – Top 10 Assignee Companies Geographic Distribution, p. 50
- Figure 3.8* – Average Citations per Patent (received vs. made) for the Top 20 Assignee Companies, p. 52
- Figure 4.1* – Kaplan-Meier Survival Curve for Wi-Fi Innovators, p. 79
- Figure 4.2* – Kaplan-Meier Survival Curve by Entry Cohort, p. 80

INTRODUCTION

In recent decades, Wi-Fi has become one of the most diffused and transformative technologies in the digital economy. From homes and offices to universities and airports, wireless connectivity has changed the way people access information and interact with digital infrastructures. Nevertheless, the success of Wi-Fi was not predictable. Contrary to other communication technologies developed under exclusive spectrum regimes dominated by incumbents, Wi-Fi emerges from a unique combination of regulatory openness, collective standardization, and market coordination.

The aim of this thesis is to analyze the economic dynamics of innovation and standardization that have guided the development and diffusion of Wi-Fi, with particular attention to how firms have used patents to participate in this technological trajectory. The analysis seeks to understand whether and how the process of Wi-Fi standardization affected firms' innovative activity, their competitive strategies, and their technological performance over time.

The analysis is based on a comprehensive dataset of over 60,000 patents related to Wi-Fi and Wireless Local Area Network (WLAN) technologies, covering almost one century of innovation (1924-2020) and including more than 200 assignee firms worldwide. This dataset makes it possible to trace the evolution of the patenting activity, to identify key turning points in the Wi-Fi innovation process, and to quantify how regulatory and industrial events, such as the 1985 FCC decision, the IEEE 802.11 standardization, and the rise of the Wi-Fi Alliance, coincided with changes in innovative output.

From the methodological point of view, the thesis combines descriptive analysis and econometric modeling. The descriptive section explores the temporal, technological, and geographic patterns of patenting, highlighting entry and exit dynamics of firms, the levels of concentration, and the patenting citations. The econometric analysis uses count models, panel regressions, and survival models to evaluate (i) the determinants of patenting activity, (ii) the relationship between patents and firm performance, and (iii) the factors that influence the persistence of firms over time.

Beyond the empirical contribution, the thesis contributes to the broader debate on the economics of standardization and technological innovation, highlighting how the Wi-Fi

case represents an emblematic example of how public policy, open standards, and corporate strategies interact to generate collective innovation and global diffusion.

The thesis is structured as follows:

- Chapter 1 analyzes the main economic literature on patents, innovation, and standardization, showing how intellectual property has evolved from a simple protection tool to a strategic and collaborative asset;
- Chapter 2 describes the context of analysis, tracing the Wi-Fi history from its regulatory origins to its industrial diffusion, identifying the key actors and events of its evolution;
- Chapter 3 presents the dataset and the descriptive statistics, offering a detailed overview of the patenting dynamics, the sectoral structure, and the technological specializations;
- Chapter 4 develops the econometric analysis, investigating the determinants, the effects, and the persistence of the firms patenting activity.

CHAPTER 1

LITERATURE REVIEW

1.1 Chapter Introduction

The debate over the economic role of patents has long accompanied the theoretical and empirical reflection on patents. Since the pioneering studies of Machlup and Penrose (1950), patents have been conceived as institutional instruments aimed at balancing two fundamental needs: on the one hand, incentivizing firms and inventors to invest in R&D by guaranteeing a period of economic exclusivity over the invention; on the other, favoring the diffusion of knowledge through the publication of innovative results. This compromise between incentive and disclosure is at the basis of our modern economic intellectual property.

Nevertheless, over the years, the rapid technological evolution and the growing relevance of immaterial assets have made it difficult to evaluate the efficiency of patents as an innovation policy instrument. The structural changes of technology-intensive sectors, in particular, the ones related to ICT, have revealed not only the potential but also the issues of the patenting system: high costs, legal uncertainty, difficulty of enforcement, and the risk of fragmentation of property rights.

In parallel, the economic literature has broadened, shifting from the analysis of patents as simple research incentives towards a more complex perspective that interprets them as instruments of appropriation, indicators of innovative activity, and strategic resources in complex technological markets. From this perspective, recent studies are not only limited to measuring the impact of patents on innovation, but they also analyze how companies use them in combination with other instruments of protection, both formal and informal, and how such instruments interact with phenomena such as technological standardization and competition in the market of information.

This chapter reconstructs the main theoretical and empirical contributions that have dealt with this subject, organizing them into three main fields.

The first one regards the literature about patents as instruments of appropriation, which analyzes the reasons that drive the choice of companies between formal protection and alternative forms such as secrecy or lead time.

The second field explores the use of patents as economic innovation indicators by focusing on the literature that values patents as a measure of inventive activity and research value.

Finally, the third field of study considers patents as strategic instruments in competitive dynamics and the processes of definition of the technological standards, with specific attention to ICT sectors and cumulative innovation phenomena.

The objective is double. On the one hand, we provide a synthesis of the main theoretical and empirical evidence relative to the use and value of patents. On the other hand, we identify the literature gap to which this thesis reconnects, that is, the analysis of the role of patents in the process of Wi-Fi standardization and its implications for the strategies of innovation of the companies involved.

1.2 Patents as Instruments of Innovation Appropriation

1.2.1 Theoretical Approaches

In the economic debate on innovation, patents have always been considered one of the main instruments companies use to appropriate returns generated by their R&D activity. The economic logic at the basis of the patenting system builds on the idea of creating an incentive to innovate, offering the inventor a temporary exclusive right, which allows internalizing part of the social benefits produced by the new knowledge. As pointed out by Machlup and Penrose (1950) the patent is considered a form of “institutional compromise” between two potentially controversial objectives: stimulate the production of new ideas and, in the meantime, guarantee their diffusion inside the economic system.

The relationship between patents and innovation comes with ambiguities. In the classic economic theory, patent protection is considered an instrument that allows correcting a market failure related to the public nature of knowledge. By the early 1990s, thanks to the evolution of complex technological sectors and the growing relevance of

cumulative innovation, several authors highlighted that excessively broad or long intellectual property rights could cause inefficiencies and slow down technological progress. According to Scotchmer (1991; 2005) industries where a single discovery represents an intermediate step in a process of continuous innovation are characterized by a “double marginalization” effect, caused by patent protection. The owner of the initial patent exercises a monopolistic power that could discourage the following developments or make them costlier.

Even the literature about the so-called “patent races” (Reinganum 1989) has demonstrated that competition to obtain a patent could lead to an excessive duplication of research efforts, thus reducing the overall system efficiency. From this perspective, a patent not only incentivizes innovation but also distorts it, inducing companies to concentrate their resources in areas where it is easier to gain legal protection, rather than where the economic and social impact of innovation would be higher.

The approach taken by Bessen and Maskin (2009) has further supported this analysis, highlighting that in contexts of sequential innovation, such as ICT and software, the absence of patents might even nurture a further diffusion of knowledge and stimulate the overall innovation. In these sectors, in fact, the cumulative nature of technological progress makes the possibility of freely using the prior inventions a greater incentive than the prospect of a monopolistic income.

Overall, the theoretical literature transforms the patent from a mere “invention reward” to an instrument of institutional balance. The purpose is not only to protect the inventor, but also to define a system that stimulates production and, in the meantime, the circulation of knowledge. Such a balance, however, is fragile and depends on the characteristics of the industrial sector, the pace of technological change, and the level of cumulative nature of the innovation. In high-technology intensive sectors, such as electronics and wireless communication, the patent tends to be mainly used as an instrument of negotiation or of strategic coordination, rather than an entry barrier.

1.2.2 Empirical Evidence

The econometric analysis of the use of patents as instruments of innovative appropriation started with a series of direct surveys on companies to understand the relative importance of the different forms of knowledge protection. The most influential contribution in this field is represented by the Yale Survey (Levin et al. 1987), which has analyzed a broad sample of manufacturing companies from the United States. This survey's results have challenged the traditional perspective of patents as mostly a defensive mechanism, highlighting instead that secrecy and lead time were considered more efficient protective instruments concerning research results in most sectors.

Only in a few fields, such as chemicals and pharmaceuticals, patents have emerged as fundamental to preserving the gains derived by innovation.

These conclusions have been confirmed and updated by the following Carnegie Mellon Survey (Cohen et al. 2000), which broadened the sample and introduced a deeper analysis of the different appropriation instruments. Also in this case companies indicated that the informal protective instruments, such as secrecy, lead time, and technical complexity, are the preferred protective mechanisms relative to patents, especially in high-speed innovative sectors. Nevertheless, research also highlights a strategic role of patents, not only as protective instruments, but also as a strategic asset for negotiation and a signal of a firm's innovative capability in technology markets. In most cases, companies patent to obtain visibility, strengthen their position in potential legal disputes, enhance their access to external loans, or defend the gains deriving from their invention.

A crucial contribution is provided by Hall, Helmers, Rogers, and Sena, who, in their literature review entitled "The Choice between Formal and Informal Intellectual Property" (Hall et al. 2012), systematize the main findings of international surveys and theoretical models on firms' choices between formal (i.e., patents, trademarks, copyrights) and informal (i.e., secrecy, lead time, complexity) mechanisms of protection. The authors show that the companies' decision is not simply binary, since it depends on a combination of internal and external factors: the nature of the innovation (product or process), the company's dimension, the enforcement costs, and the sectoral context. In particular, the product innovations, which can be more easily imitated, tend to be protected by patents,

while the process innovations are more suited to secrecy protection. Moreover, the big companies are more likely to use formal protection than small and medium-sized companies, which are mainly focused on informal instruments, due to the costs and the complexity of the patenting process.

The most recent literature suggests that patents and secrecy are not necessarily substitutes, since they are often used as complementary instruments. In many sectors, companies patent to obtain public recognition and legal deterrence, while keeping the key information that guarantees a competitive advantage reserved. This mixed strategy is particularly diffused in ICT and high-tech sectors, characterized by cumulative innovation and shared technological standards, where formal protection is also necessary to participate in standardization processes or to reinforce their negotiating power within the industry alliances and standard-setting consortia.

Overall, empirical evidence agrees on an essential point. The choice of the appropriation mechanism is determined not only by the legal effectiveness of the patent, but also by a strategic balance between costs, risks, and benefits. Patents constitute, thus, a crucial but not an exclusive part of how companies protect and value their innovations. This perspective provides the basis for correctly interpreting the patenting activity observed in high-technology sectors, such as the Wi-Fi sector, in which the borders between innovation, standardization, and company strategy are deeply interconnected.

1.3 Patents as Economic Indicators of Innovation

1.3.1 The use of patents as a proxy for innovative activity

The measurement of innovation is one of the most relevant struggles in the knowledge economy. The innovative activity is intangible thus it is not always possible to directly observe it using accounting or productivity indicators. Because of this, since the 1970s and systematically since the 1980s, patents have been progressively adopted by economists as a quantitative proxy of innovative activity (Griliches, 1990; 1998). On the one hand, the patenting data are publicly accessible, and they cover long temporal periods. On the other hand, each patent represents a codified expression of an innovative act, with detailed information about inventors, title holders, dates, technological classifications, and citations.

In his seminal contribution, “Patent Statistics as Economic Indicators” (Griliches 1990), the author provides a critical overview of the use of patents as a measure of innovation, highlighting both their potential and their limitations. On the one hand, patents provide an objective measure of the inventive output, and they can be aggregated to analyze the technological dynamics at the firm, sector, or country level. On the other hand, the heterogeneity of their economic value and the different patenting inclination between industries make a direct comparison more difficult. Not all innovations are patented, and not all patents represent economically significant innovations: many of them have a strategic, defensive, or purely signaling value (Hall et al. 2012).

The differences in patenting propensity depend on multiple factors: the type of innovation (product or process), the company dimension, the industrial sector, the appropriability regime, and the structure of market competition (Levin et al. 1987; Cohen et al. 2000). In high-technology industries, such as ICT and electronics, patenting is often used as a defensive or portfolio strategy, rather than a pure legal protection mechanism. By contrast, in more “discrete” sectors, such as chemicals and pharmaceuticals, where each innovation is more isolated and easier to patent, patents represent a more reliable indicator of actual R&D activity.

Another limitation outlined by Griliches regards the institutional heterogeneity of the patenting systems. Differences regarding examination procedures, registration costs, protection duration, and the severity of patentability criteria can compromise the data comparability across countries or over time. Moreover, the growing strategic emphasis on patent ownership observed over the past few decades has generated a phenomenon described as *patent inflation* (Kortum and Lerner, 1999), that is, an increase in the number of patent filings that does not necessarily correspond to a genuine rise in technological innovation.

Despite such limitations, the literature agrees on recognizing patents as a unique informative source for studying innovation, especially if analyzed through sophisticated metrics. Patent citations (Trajtenberg et al. 1993; Hall et al. 2005) represent, for example, an indicator of the quality or the technological impact of an invention, since they reflect the diffusion and the influence of a patent over time. Similarly, the IPC (International Patent

Classification) and the relationships among co-inventors and co-owners allow us to study the technological specialization and the innovative collaborations.

The use of patents as economic indicators, therefore, requires a balanced approach. Although they are not a perfect measure of innovative activity, they provide a standardized and structured set of data that makes it possible to analyze technological dynamics and innovative competition among firms. In the context of this thesis, which examines innovation trajectories related to the standardization of Wi-Fi technology, patents serve both as a quantitative indicator of inventive activity and as a qualitative lens through which to observe the technological evolution of firms involved in standardization processes.

1.3.2 Relationship between R&D and patenting output

One of the main contributions of the empirical evidence regarding innovation consists of analyzing the relationship between the inputs of R&D and the patenting output. Since the 1980s, several authors have tried to quantify this relationship to evaluate how much patents represent a trustworthy indicator of innovative activity.

Among the most influential contributions, the works of Pakes and Griliches (Pakes and Griliches 1980) and Bound et al. (Bound et al. 1984) laid the foundations for the so-called *knowledge production function*, a model that links R&D inputs to the technological outputs generated by firms.

The results of this research demonstrate that the correlation between R&D and the number of patents is generally strong in cross-sectional analysis, where different companies or sectors are compared at a certain moment, while it tends to be weaker in time-series analysis, which follows the same company over time. This difference suggests that, while R&D expenditures effectively explain cross-sectional variations in firms' innovative productivity, they fail to fully capture temporal fluctuations driven by strategic, institutional, or cyclical factors.

In their study, Hall, Griliches, and Hausman (Hall et al. 1986) further analyzed this relationship by analyzing the dynamics of time lags between R&D investments and patent production. The authors show that the effects of research activity emerge with a certain temporal delay and that the distribution of these lags varies according to the industrial

sector and the size of firms. The introduction of panel models with individual effects made it possible to account for unobserved heterogeneity, improving the accuracy of the estimates and confirming the existence of a positive, even though not immediate, relationship between R&D and patent output.

Further empirical evidence, such as that provided by Hausman, Hall, and Griliches (Hausman et al. 1984b), shows that companies with more R&D intensity tend to generate more patents, even though this relationship is not linear: the marginal return on research investment decreases beyond a certain threshold. This implies that the effectiveness of R&D expenditures in generating patentable innovation depends not only on the absolute level of spending, but also on the efficiency of organizational processes, the quality of human capital, and the competitive environment in which the firm operates.

An additional aspect examined in the literature concerns the sectoral differences in the patent productivity of R&D. In more “discrete” technological sectors, such as chemicals or precision mechanics, a single innovation can often result in a patent directly linked to specific research efforts. In contrast, in more “cumulative” industries, typical of electronics and information technology, the relationship is more complex, as R&D activity frequently leads to incremental innovations that are not always patented individually but collectively contribute to technological progress.

Overall, the empirical literature shows that patents are reliable indicators of innovative output when interpreted within the appropriate economic and sectoral context. They reflect not only the tangible outcomes of research activity but also the strategic and institutional factors shaping firms’ use of intellectual property. For this reason, the analysis of patent data should be accompanied by a careful consideration of the underlying R&D mechanisms that generate them, so as to avoid misleading interpretations.

Within the framework of this thesis, the relationship between R&D and patent output represents a fundamental starting point for understanding the evolution of innovation among firms involved in the standardization of Wi-Fi technology. Examining how research investments translate into patenting activity makes it possible to identify the stages in which the development of the standard has amplified or reshaped the sector’s innovative productivity.

1.3.3 Patent Citations and Economic Value

Instead of counting how many patents a firm owns, many studies have focused on patent citations to understand the quality and impact of innovation. Patent citations are the references to previous patents included in new applications, and they show to what extent an invention has been used, mentioned, or influenced later technological developments. In this sense, citations are considered an indirect measure of the technological importance and diffusion of knowledge created by an invention (Jaffe et al. 1993).

Using patent citations as an indicator of knowledge flows comes from the analogy with scientific publications. When a patent receives many citations, it usually means that the knowledge behind it has been useful or has influenced other innovations. In their study, Jaffe, Trajtenberg, and Henderson (Jaffe et al. 1993) found that patent citations are often geographically localized, which means that innovation spillovers are stronger among firms and institutions that are close to each other. This result shows that citations can capture not only the technological relevance of an invention, but also how knowledge spreads across regions.

Later, Hall, Jaffe, and Trajtenberg (Hall et al. 2005) extended this analysis by studying the link between the market value of firms and the number of citations received by their patents. They found a positive and significant correlation between citation counts and market value, suggesting that patents that are cited more often tend to be economically more valuable. As a consequence, patent citations can be used as a proxy for the economic value of innovation, since they reveal a patent's ability to shape technological progress and create economic benefits for the firm.

However, using citations as an indicator also has some limits. Not all citations really represent technological influence, because some are added by patent examiners instead of inventors, and others depend on legal or institutional rules. In addition, the distribution of citations is very uneven; most patents receive only a few citations, while a small number of them are cited very frequently, creating a long-tail distribution.

Even with these limits, patent citations remain one of the most useful tools to study the qualitative side of innovation. When combined with patent counts, they help to capture both the quantity and the quality of inventive activity, giving a more complete view of technological performance and value creation.

In this thesis, Wi-Fi-related patents are examined not only by their number, but also by how many times they are cited. This makes it possible to identify which firms and inventions contributed the most to the development of the Wi-Fi technological trajectory. Studying citation patterns helps us understand which companies were more influential and how knowledge circulated during the Wi-Fi standardization process.

1.4 Patents as Strategic Assets and Tools of Competition

1.4.1 Patents, Firm Strategy, and Technological Markets

Beyond their role as protective instruments and indicators of inventive activity, patents also play the fundamental role of strategic resources in firms' competitive behavior. Over time, the functions of patents have evolved: from simple defensive instruments against imitation, they became key assets for negotiation, cross-licensing, and market positioning.

As outlined by Hall and Harhoff (2012), patents have progressively turned into tradable intellectual assets, often used to signal the company's technological strength or to support its financial evaluation.

In high-technology sectors, the accumulation of broad patenting portfolios has become a common strategy to reinforce the firms' negotiating position and to prevent potential litigation. The concept of "strategic patenting" describes this phenomenon: firms deposit patents not necessarily to protect a single invention, but rather to create a defensive barrier or to gain an advantage in licensing agreements. This behavior was clearly described by Hall and Ziedonis (2001) in their study about the semiconductor industry, which introduced the concept of the "patent paradox": despite the high costs and the legal uncertainties associated with patenting, companies keep increasing their patenting activity. The explanation lies in the strategic value of patents as instruments of negotiation, reputation, and technological control.

The literature also discusses the emergence of the so-called “patent thickets”, described by Shapiro (2001) as dense webs of overlapping intellectual property rights that hinder firms from commercializing new technologies without violating pre-existing patents. In many sectors, such as ICT, this leads to the emergence of complex cross-licensing, patent pools, and sometimes to hold-up or royalty stacking problems, as analyzed by Lemley and Shapiro (2007). These dynamics show that patents can simultaneously promote and hinder innovation: on the one hand, they encourage the diffusion of knowledge; on the other, they might generate transaction costs and barriers to entry for smaller firms.

In this strategic context, the role of patents goes beyond their legal function. They are part of broader technological markets, in which firms trade, license, and accumulate intellectual property as a way to control access to key technologies and to secure their bargaining power. The rise of specialized intermediaries and of secondary markets for technology has reinforced this tendency, especially in knowledge-based sectors.

For all these reasons, understanding patents as strategic assets is crucial to interpreting the behavior of firms in the ICT sector. In the specific case of Wi-Fi technology, the patenting strategies were also aimed at influencing the definition of the technical standards and securing a position in the global webs of innovation, other than protecting the single inventions. The accumulation of patents related to Wi-Fi reflects both the technological progress and a precise strategic positioning in the broader ecosystem of wireless communication.

1.4.2 Patent Thickets and Defensive Patenting

In recent decades, the growing number of patents in high-technology sectors has led to the emergence of the so-called “patent thickets”, namely dense networks of overlapping intellectual property rights, which hinder the development of new products without risking the violation of pre-existing patents. As described by Shapiro (Lemley and Shapiro 2007), patent thickets generate the so-called “tragedy of the anticommons”, where too many overlapping exclusivity rights hinder the efficient use and combination of technologies. This situation often forces firms to engage in complex negotiations, cross-licensing agreements, or the creation of patent pools to obtain access to essential technologies.

In semiconductors, telecommunications, and software industries, these dynamics have favored the emergence of defensive patenting strategies. Instead of patenting only to protect real inventions, many firms file patents to deter litigation, negotiate from a stronger position, or prevent competitors from patenting correlated inventions. Hall and Ziedonis (Hall and Ziedonis 2001) documented this behavior in their study of the U.S. semiconductor industry, showing how even firms that used to rely on trade secrets began to expand their patent portfolios after changes in intellectual property enforcement increased the perceived risk of litigation. This phenomenon, referred to as the “patent paradox”, highlights how a stronger patent regime does not necessarily reduce the patenting activity, but can, paradoxically, encourage it.

Defensive patenting might also lead to royalty stacking and hold-up problems, as Lemley and Shapiro (Lemley and Shapiro 2007) show. When different patents cover complementary technologies, each patent holder may request separate licensing fees, increasing the total cost of innovation. At the same time, firms controlling key technologies can exploit their position to delay their competitors or to demand excessive royalties once a technology or a standard has been diffused. This behavior alters competition and may discourage market entrance by smaller companies or new innovators.

To mitigate these issues, various institutional solutions have been developed, such as patent pools and standard-setting organizations (SSOs), where firms agree to license their essential patents under Fair, Reasonable, and Non-Discriminatory (FRAND) terms. However, the balance between protecting intellectual property and ensuring open access to technologies remains difficult to reach. Patent thickets represent one of the most evident paradoxes of the modern systems of innovation: on the one hand, intellectual property rights are meant to encourage innovation, on the other, their excessive proliferation can generate uncertainty, high costs, and inefficiency.

Understanding these mechanisms is particularly relevant in the context of Wi-Fi standardization, where various firms may hold complementary patents essential for the standard implementation. The interactions between these firms, through licensing, cross-licensing, and participation in standard-setting consortia, show how strategic patenting can both enable and constrain technological progress. In this sense, the Wi-Fi case represents a

clear example of how the innovation results are influenced not only by the technological capabilities but also by the strategic management of intellectual property rights.

1.4.3 Patents and the Structure of Technological Markets

The evolution of the role of patents not only limits them to defensive or negotiation strategies, but rather extends to their function within technology markets, that is, contexts where knowledge and intellectual property are traded, licensed, or used as economic assets. In these markets, patents represent both protection instruments and also tradable goods that allow firms to capture the economic value of their inventions and to access complementary technologies developed by other market players.

According to Arora, Fosfuri, and Gambardella (Arora et al. 2001), the growing importance of technology markets has transformed the nature of the innovative competition. Firms no longer innovate only internally but operate within an ecosystem where knowledge can be bought, sold, or exchanged. This “modularization” of innovation allows the reduction of development costs, the acceleration of the technological cycles, and fosters the diffusion of new solutions, but at the same time, it increases the dependence on solid and well-defined intellectual property regimes.

In this context, patents become instruments of technological intermediation, used to build alliances, negotiate licensing agreements, and attract investment. Hall and Harhoff (2012) highlight that, in knowledge-based industries, patent portfolios may serve as signals of a firm’s innovative capability and as guarantees for investors or potential partners. In the same way, the literature on the markets for technology shows how firms with strong research capabilities may specialize in the generation of new technologies rather than producing them directly, leading to an increasingly integrated and interdependent knowledge economy.

Nevertheless, the growing “financialization” of intellectual property rights has also introduced new struggles. The diffusion of specialized intermediaries, such as patent brokers and patent monetization firms (sometimes referred to as “patent assertion entities”), has made the competitive landscape more complex. These actors often operate with purely speculative objectives, focusing on the financial exploitation of patents rather

than their technological use. This trend raises concerns about the efficiency of the intellectual property system and the risk that the increasing “patent density” might end up slowing, rather than promoting, innovation.

In the case of Wi-Fi technology, technology markets have played a decisive role. Firms involved in the standardization process not only developed proprietary innovations but also exchanged, integrated, and made them compatible through licensing agreements and strategic collaborations. Therefore, Wi-Fi-related patents should not be interpreted merely as tools of protection or competition but as negotiation assets that allowed firms to position themselves within a global innovation network based on both technical cooperation and strategic competition.

1.5 Technological Standards, Innovation, and Patents

1.5.1 The Economics of Technological Standards

The technological standards play a fundamental role in defining how innovations are created, adopted, and diffused in the different industrial sectors. A standard can be defined as a set of shared technical rules or specifications that ensure compatibility and interoperability among products or systems realized by various firms. Standards are essential to reducing uncertainty, favoring market coordination, and generating network effects, especially in sectors characterized by rapid technological changes and a strong interdependence among components.

As outlined by Farrel and Saloner (1985, 1986) and by David and Greenstein (1990), the economics of technological standards is based on a balance between competition and compatibility. On the one hand, standards encourage the diffusion of technologies and improve efficiency by enabling products to work together and reduce duplication. On the other hand, they may create lock-in effects and market dominance if a single standard becomes entrenched and limits the future technological variety. For this reason, standardization is not purely a theoretical process, but also a strategic one, because firms compete to ensure that their technologies become part of the dominant standard.

In network industries such as telecommunications and computing, standards generate strong network externalities: the value of a certain technology increases with the number of

users adopting the same standard. This incentivizes firms to coordinate on compatible technologies and engage in strategic standard-setting behavior, where participation in standardization processes becomes a means to influence market structure and future innovation paths.

The literature generally distinguishes between market-based standards, which emerge naturally through competition (like the case of VHS and Betamax), and committee-based standards, which are developed collectively within Standard-Setting Organizations (SSOs) such as IEEE, ETSI, or ISO. In the second case, since several firms are involved, it becomes important to manage intellectual property rights, because many of the technologies included in a standard are protected by patents. The relationship between patents and standards has become a central topic in the literature, exploring how the inclusion of patented technologies in a standard can influence innovation, diffusion, and competition.

In the case of Wi-Fi, the standardization process played a key role. The IEEE 802.11 family of standards was not developed by a single company but resulted from collaboration among many firms contributing different technologies. Many of these technologies were patented, creating a complex mix of cooperation and competition among the firms involved. Understanding this process is crucial to explaining how Wi-Fi evolved from a niche innovation into one of the most widely adopted technologies in wireless communication.

1.5.2 Patents and Standardization Processes

The relationship between patents and technological standards is a very important topic in the study of innovation. When a patented technology becomes part of a standard, it turns into what is called a Standard-Essential Patent (SEP), meaning that it is necessary to use that patent to implement the standard, and there are no real alternatives. This creates both good and bad effects. On the positive side, including patented technologies in standards helps new inventions spread faster and ensures that products from different companies can work together. On the negative side, it can give too much market power to the firms that own these patents, since everyone else needs to use their technology to stay compatible with the standard.

To deal with this problem, Standard-Setting Organizations (SSOs) like IEEE or ETSI have introduced some rules. Companies that take part in creating a standard have to declare their patents and agree to license them under Fair, Reasonable and Non-Discriminatory (FRAND) terms. As explained by Lerner and Tirole (2004), patent pools and FRAND agreements help reduce negotiation costs and make it easier for firms to get access to the technologies they need. Still, these agreements are not always easy to manage, and they can create problems if some firms try to collude or exclude competitors.

The literature usually presents two views on SEPs. The pro-competitive view says that SEPs make it easier for technologies to spread and give firms a stable framework to innovate. The anti-competitive view, instead, argues that firms owning SEPs might take advantage of their position by asking for very high royalties after the standard is adopted, a behavior known as patent hold-up. According to Bekkers and Martinelli (2012), this is quite common in the ICT sector, where a small number of large firms hold most of the essential patents and therefore have a strong influence on how technologies evolve.

Blind et al. (2010) argue that patents and standards should be seen as complementary rather than opposed to each other. Standards rely on patents because they include the newest and most advanced technologies, while patents benefit from standards because they reach a larger market. The main challenge is to ensure that the rules inside SSOs are fair, transparent, and balanced, so that all firms have an incentive to share their technologies and contribute to the standard.

In the case of Wi-Fi, this balance is very clear. The IEEE 802.11 standard was created thanks to the collaboration of many firms, each contributing its own patented technologies. Some of these companies joined the process not only for technical reasons but also to gain visibility and opportunities for licensing. The FRAND commitment made it possible for Wi-Fi to spread quickly and become a global, interoperable technology. At the same time, it also created a competitive environment where access to essential patents became a central part of firms' innovation and market strategies.

1.5.3 Innovation Dynamics in ICT Industries

Innovation in the ICT sector usually develops cumulatively. New inventions often come from earlier ones, creating a long chain of improvements over time. Because of this,

patents have an important role, not just to protect new ideas but also to influence how future technologies can evolve. As Bessen and Maskin (2009) explain, when innovation is cumulative, too much patent protection can sometimes slow things down, because it makes it harder for other firms to build on existing knowledge.

ICT markets move very fast and are full of connections between different companies. This means that firms often need to work together and compete at the same time. Large firms tend to register many patents, not only to protect what they invent but also to use them in negotiations or collaborations. Ziedonis (2004) shows this clearly in her study on the semiconductor industry, where many firms started to patent more and more to strengthen their position and protect themselves in a competitive environment.

In industries like telecommunications and computing, innovation is rarely the result of one firm working alone. It happens through networks of companies, universities, and organizations that set standards and share knowledge. These collaborations help combine different technologies and create compatibility between products, but they can also bring conflicts about who controls the intellectual property and who can use it. The presence of Standard-Essential Patents (SEPs) makes this even more complicated, since firms sometimes need to use technologies owned by their competitors.

The story of Wi-Fi shows well how these processes work. The IEEE 802.11 standard was developed thanks to many companies that decided to contribute their patented technologies. Some joined early and influenced the direction of the standard, while others came later and adapted their strategies to the existing framework. Collaboration was essential to make the technology work for everyone, but competition never disappeared, since firms also wanted to lead the market for Wi-Fi products and related innovations.

Overall, innovation in ICT industries shows how patents, cooperation, and standardization are strongly connected. Patents can help innovation when firms also share and collaborate, while standardization allows new technologies to spread faster. The Wi-Fi case is a clear example of this balance, where competition and collaboration worked together to make a global technology possible.

1.6 Chapter Conclusions

This chapter has systematically reviewed the main aspects tackled by economic literature on patents, showing how their role has evolved from a simple protective instrument to a strategic asset in technological markets and standardization processes.

In the first part, patents have been analyzed as instruments of appropriation, highlighting the balance between providing incentives for innovation and promoting knowledge diffusion. Theoretical studies (Machlup and Penrose 1950; Scotchmer 1991; Bessen and Maskin 2009) and empirical evidence, such as the historical Yale and Carnegie Mellon Surveys, show that the effectiveness of patents in protecting innovation varies across sectors and depends on firms' technological and competitive characteristics.

The second part focused on patents as economic indicators of innovation. Following the approach of Griliches (1990), patents were considered a useful but imperfect proxy for innovative activity, which becomes more meaningful when complemented with measures of quality and technological impact. Patent citations (Jaffe et al. 1993; Hall et al. 2005) emerged as an important indicator of the economic relevance and diffusion of knowledge, helping to distinguish between the quantity and quality of inventive activity.

The third section explored the strategic dimension of patents, emphasizing their use as market resources and negotiation tools. The studies by Hall and Ziedonis (2001) and Shapiro (2001) showed that the proliferation of intellectual property rights can create patent thickets and defensive patenting, especially in high-tech sectors. At the same time, studies on technology markets (Arora et al. 2001) have shown that patents have turned into tradable assets, used to form alliances, attract investment, and strengthen firms' bargaining power.

Finally, the chapter has delved into the relationship between patents, technological standards, and innovative dynamics, showing how standardization affects both diffusion and knowledge appropriation mechanisms. Studies by Farrel and Saloner (1985, 1986), Lerner and Tirole (2004), and Bekkers and Martinelli (2012) demonstrated that participation in standardization processes allows firms to integrate innovation and cooperation and acquire a strategic role in defining technological trajectories.

Overall, the literature suggests that innovation in ICT sectors, especially in the Wi-Fi case, is driven by the interaction between competition and cooperation, and between protection and knowledge sharing. Patents are not only instruments of protection, but also key elements in collective processes of innovation and standardization.

This analysis provides the theoretical foundation for the empirical analysis that follows. The next chapter introduces the context of analysis, describing the technological, institutional, and industrial environment in which Wi-Fi emerged and developed. Understanding this background is essential to interpreting the empirical results that follow, since the structure of the industry and the dynamics of standardization have strongly influenced how firms have used patents to innovate and compete.

CHAPTER 2

CONTEXT OF ANALYSIS: THE Wi-Fi INDUSTRY

2.1 Chapter Introduction

Wi-Fi is one of the most widespread technologies worldwide, since it grants Internet access without wires in several places like homes, offices, universities, airports, and public spaces. Despite this, the extent of Wi-Fi growth and establishment was not predictable. In fact, this technology did not follow the standard evolutionary path of other innovations in the telecommunications sector, which were born in rigid licensed-spectrum regimes, characterized by incumbents' dominance. On the contrary, Wi-Fi resulted from a unique combination of political decisions, new standardization processes, and market dynamics.

The regulatory roots of Wi-Fi are the first distinctive element in its evolutionary path. In 1985, the United States' Federal Communications Commission (FCC) took an unprecedented decision: "[...] it opened the 915 MHz, the 2.4 and 5.8 GHz bands designated for industrial, scientific and medical (ISM) applications for the use by radio systems, under the condition that spread spectrum techniques would be used" (Hayes and Lemstra 2009, 58).

This initiative has created an "[...] unlicensed commons for various forms of wireless communication applications" (Negus and Petrick 2009, 36). Therefore, a new Wi-Fi ecosystem could develop, with millions of Wi-Fi devices sold and over 206,000 Wi-Fi hotspots worldwide. As observed by Hayes and Lemstra (2009), this choice reduced the entry barriers and stimulated innovation by start-ups and small producers, opening the path for a competitive and heterogeneous ecosystem.

The second crucial step was the process of technological standardization. In 1990, the IEEE (Institute of Electrical and Electronics Engineers) established the 802.11 working group to develop a common standard for Wireless Local Area Networks (WLANs). After years of debate and compromise, the first version of the 802.11 (1-2 Mbps) standard was approved in 1997 (Hayes and Lemstra 2009: 61-62). The decisive aspect was not only

technological, but also strategic: creating open standards allowed interoperability among products by different producers. This generated a network effect. The more compatible devices entered the market, the more users found Wi-Fi adoption convenient, thus incentivizing firms to develop new products.

Finally, the spread of Wi-Fi was consolidated by the actions of key industrial actors. In 1999, Apple made the strategic decision to incorporate wireless networking as a key feature in the new iBook laptop, making the Wi-Fi market more accessible to consumers (Hayes and Lemstra 2009: 64-65). In the same year, the Wi-Fi Alliance (initially Wireless Ethernet Compatibility Alliance, WECA) was born, ensuring interoperability among products based on the IEEE 802.11 standard and creating a recognizable brand worldwide (Hayes and Lemstra 2009: 65-66). A few years later, in 2003, Intel made Wi-Fi integrated in laptops by default, through the Centrino program, which transformed it from a niche technology into a universal standard (Hayes and Lemstra 2009: 66).

This chapter aims to define the fundamental steps, from regulation to standardization and market dynamics, that enabled the Wi-Fi affirmation worldwide. This chapter is not only valuable from the theoretical point of view, but also functional to the empirical analysis since the crucial steps will be used as breakpoints in the analysis of the patents data to verify if they coincided with an increasing innovative activity.

Briefly, the history of Wi-Fi shows how a radical innovation was born from the interaction between public policies and industrial initiatives. This is, in fact, an example of a policy-driven innovation. Without the regulatory opening of 1985 and without the development of an open standard, the mass diffusion of Wi-Fi would have not been possible.

2.2 The Regulatory Roots of Wi-Fi

The origins of Wi-Fi can be traced back to a radically innovative institutional approach, unlike other communication technologies that developed under exclusive spectrum regimes dominated by incumbents.

The real turning point that ensured the emergence of Wi-Fi was a regulatory decision. In 1985, the United States' Federal Communications Commission (FCC)

authorized the unlicensed use of three frequency bands: 902–928 MHz, 2.4–2.4835 GHz, and 5.725–5.875 GHz, which were initially reserved for industrial, scientific, and medical (ISM) applications. As stated by Negus and Petrick, “[...] the FCC’s initiative to create an ‘unlicensed commons’ for various forms of wireless communication applications has been the key enabler of today’s multi-billion dollar per year WLAN industry” (Negus and Petrick 2009: 36).

The decision was revolutionary for two reasons. Firstly, this was the first time a national agency authorized radio communication on an unlicensed basis, that is, without requesting operators to purchase exclusive rights on the spectrum. Consequently, it reduced the entry barriers by allowing small businesses and start-ups to experiment with wireless applications without sustaining licensing costs.

Secondly, the agency imposed some technical constraints to avoid the risk of frequency congestion. However, the rules introduced in the First Report and Order (FRO) in 1985 were deliberately simple to enable technological flexibility. This approach allowed interoperability in the ISM bands, imposing only minimal technical constraints to prevent harmful interference, such as a 1 Watt maximum peak output power to ensure that transmissions remained local rather than nationwide; they had to suppress sideband emissions to avoid disturbing adjacent channels; they were required to use spread spectrum techniques, such as frequency hopping or direct sequence modulation, which distributed the signal across a wider bandwidth to improve robustness and enable multiple users to share the same spectrum (Negus and Petrick 2009: 38).

This “light-touch” regulation enabled incentivizing innovation on the one hand, while limiting interference risks on the other, becoming a truly facilitating factor in the Wi-Fi industry.

In Europe, the path was quite different. During the 1990s, the European Telecommunications Standards Institute (ETSI) and the Conference of European Postal and Telecommunications Administrations (CEPTA) developed the family of the HIPERLAN (High Performance Radio Local Area Network) standard. The first standard, HIPERLAN/1, was published in 1997, followed by HIPERLAN/2 in 2000. However, the adoption was slower and less competitive than in the United States, since the HIPERLAN products were too late and too expensive to compete with the mature IEEE 802.11 standard (Hayes and Lemstra 2009: 63). In fact, despite their technical sophistication, the

HIPERLAN devices weren't able to compete with the economies of scale and the rapid diffusion of Wi-Fi.

The trajectory difference between the United States and Europe highlights the decisive role of public policy in shaping innovation. In the United States, the flexible and non-exclusive approach incentivized many actors to enter the market. On the contrary, in Europe, a more centralized and costlier approach delayed the technology diffusion.

From a broader perspective, Oh highlights the crucial role of spectrum policy regimes in shaping innovation. In particular, “[...] licensed regimes generally refer to the use of frequencies on an exclusive basis; unlicensed is where wireless access is non-exclusive” (Oh, 2020: 39).

In the case of Wi-Fi, the absence of exclusive property rights acted as an innovation catalyst, enabling a variety of actors to enter the market and creating the conditions for a dynamic and open market, in which innovation rapidly diffuses.

In sum, the 1985 FCC's decision can be considered the true act of birth of Wi-Fi, since it created the regulatory framework that enabled IEEE 802.11 standardization and subsequent industrial adoption.

2.3 The IEEE 802.11 standard

The regulatory opening introduced by the FCC in 1985 allowed experimentation, even though it would not have been possible without a standardization process that would enable interoperability among devices. In the following years, the lack of a common protocol hindered the widespread adoption of Wireless Local Area Networks (WLANs). Each producer developed proprietary solutions, often incompatible with each other, causing market fragmentation.

In this context, in 1990, the Institute of Electrical and Electronics Engineers (IEEE) established the 802.11 working group, intending to define an open standard for the WLANs (Hayes and Lemstra 2009: 61).

The work of the committee came with internal tensions, too. Two different technological approaches competed for primacy: Frequency Hopping Spread Spectrum (FHSS), which was simpler and more robust, but limited in its performance, and Direct

Sequence Spread Spectrum (DSSS), which was more difficult to implement but had higher data rates. After a long debate, the initial standard included FHSS and DSSS techniques to find a solution to the lack of consensus on which technique was superior (Negus and Petrick 2009: 40-41).

In 1997, the first official version of the IEEE 802.11 standard was approved, offering transmission speeds of 1-2 Mbps. While this was an important goal, its limited performance initially hindered its large-scale adoption. Nevertheless, the real turning point came shortly afterward, with the 802.11b and 802.11a extensions. The former, approved in 1999, allowed data rates up to 11 Mbps in the 2.4 GHz band, while the latter achieved 54 Mbps in the 5 GHz band. These technological evolutions marked the transition from a niche technology to a competitive solution with respect to wired connectivity (Negus and Petrick 2009: 44).

In parallel, the problem of interoperability between products by different manufacturers emerged. In fact, a formal standard wasn't adequate to guarantee interoperability between different products, because implementation differences could compromise compatibility. To address this issue, the Wireless Ethernet Compatibility Alliance (WECA) was founded in 1999 and later renamed "Wi-Fi Alliance". As stated by Negus and Petrick, "[...] the 'Wireless Ethernet Compatibility Alliance' (WECA) was formed about this timeframe and provided a multi-vendor interoperability certification mechanism for 802.11b products. WECA also promoted the trademark 'Wi-Fi' (known as Wireless Fidelity) " (Negus and Petrick 2009: 47).

The contribution of Wi-Fi Alliance was double. On the one hand, it introduced the certification program "Wi-Fi CERTIFIED", which verified interoperability among devices, offering consumers the guarantee that products from different brands could function together. On the other hand, it transformed a technical name such as "IEEE 802.11b" into a global recognizable brand, "Wi-Fi", which was simple to remember and to communicate.

The creation of the Wi-Fi brand by WECA in 1999 was crucial for market acceptance, since it turned a technical standard into a consumer-friendly label. (Negus and Petrick 2009: 65).

Thanks to the combined process of standardization and branding, Wi-Fi soon acquired credibility in the eyes of both producers and users. On the supply side, technology firms increasingly invested in developing compatible devices; on the demand side, consumers began to rely on a recognizable brand that ensured interoperability and quality. In this sense, the role of Wi-Fi Alliance was decisive in triggering the network effects: the greater the number of certified products available on the market, the more convenient adoption became for users, which in turn stimulated further innovation by firms.

In conclusion, the standardization of IEEE 802.11 marked the second decisive turning point, following the FCC's regulatory decision. While the FCC's 1985 decision had lowered entry barriers and enabled experimentation with inexpensive wireless solutions, the open IEEE standard, together with the Wi-Fi Alliance's certification system, transformed the technology into a scalable and universally adoptable solution. Taken together, these factors laid the foundation for the spread of Wi-Fi on a global scale and prepared the ground for the market dynamics that unfolded between the late 1990s and the early 2000s.

2.4 Market Dynamics and Wi-Fi Adoption

The process of standardization and the creation of the Wi-Fi Alliance created the necessary conditions for the diffusion of Wi-Fi, but its mass adoption was the result of market dynamics that turned Wi-Fi from a niche solution into a global phenomenon. In the early 1990s, some pioneering companies tried to design WLAN products. WaveLAN, introduced by NCR and later commercialized by Lucent, was mainly designed for business applications such as the Point of Sale (POS) system in supermarkets. However, these devices were too expensive and had limited performance, which hindered their adoption. As Hayes and Lemstra report, "prospective customers appeared to be fascinated by the technology, but the benefits were perceived as marginal and the price at US\$1,390 per card as too high." (Hayes and Lemstra 2009: 64)

Despite their limits, these early attempts demonstrated the feasibility of the technology and prepared the ground for future development.

The turning point came in 1999, when Apple launched the iBook integrated with the AirPort card based on the IEEE 802.11b standard. For the first time, wireless technology was embedded in a consumer product, breaking the barrier that had confined it to business

or academic environments. In fact, Hayes and Lemstra note, “[...] the product was launched as the Apple Airport in the summer of 1999, with the PC card priced at US\$99 and the access point at \$299. At this price level, the 11 Mbit/s Wireless LANs could compete effectively with the 10 Mbit/s wired Ethernet.”(Hayes and Lemstra 2009: 65). With this launch, Wi-Fi began to enter homes, mainly because of Steve Jobs’ strategic vision to make wireless connections part of the domestic technological experience.

Apple opened the doors to consumer adoption, but Intel was the one responsible for making Wi-Fi a universal standard. In 2003, the company introduced the Centrino program, a brand that combined a mobile processor, an optimized chipset, and an integrated Wi-Fi card. For the first time, Wi-Fi became an integrated part of laptops, rather than an optional accessory. “This marks the ultimate success of Wi-Fi, having moved from PC adaptors, through plug-ins and integrated chipsets, to functionality that has become part of the hardware core of laptop computers.” (Hayes and Lemstra 2009)

Intel invested substantial resources in a global marketing campaign that promoted the freedom of wireless connection, consolidating Wi-Fi as an essential technology for mobility.

At the same time, the expansion of public hotspots accelerated Wi-Fi adoption. From the early 2000s onward, chains such as Starbucks, together with airports and hotels, began to offer wireless connections to their clients. This evolution contributed to transforming Wi-Fi from a household solution into a service increasingly available in public spaces. Hayes and Lemstra observe that “[...] it has been the Starbucks initiative to provide wireless access to the internet in their coffee shops that has set off Wi-Fi as the preferred means of accessing the internet in public areas in general.”(Hayes and Lemstra, 2009: 66)

The idea of accessing the Internet on the move became more and more rooted, further reinforcing network effects.

Another major phenomenon that contributed to Wi-Fi adoption was the development of community initiatives and municipal networks. Community initiatives were bottom-up projects in which groups of citizens, volunteers, or local associations built and maintained Wi-Fi networks. Their purpose was to share Internet access and create a sense of digital community. A notable example is Wireless Leiden in the Netherlands (2001), one of the first large-scale community Wi-Fi networks in Europe. Municipal networks, by contrast,

were ‘top-down’ projects led by local governments that aimed to provide Wi-Fi as a form of public service. The most famous example was the Philadelphia project (2004), which aimed to provide low-cost Wi-Fi access to all residents. Even though these projects were not sustainable in the long run, they contributed to reinforcing the perception of Wi-Fi as an inclusive technology, capable of expanding beyond the borders of business and domestic networks. (Hayes and Lemstra, 2009)

Overall, the adoption of Wi-Fi can be seen as a prime example of how market dynamics, combined with open standards and effective branding, can create a self-reinforcing cycle of technological diffusion. The credibility gained through the Wi-Fi label, the cost reductions enabled by economies of scale, and the increasing availability of devices and public infrastructures transformed Wi-Fi, in just a few years, from an emerging technology into a global infrastructure essential to the digital age.

2.5 Winners and Losers of Standardization

The process of standardization of IEEE 802.11 and the subsequent diffusion of Wi-Fi reshaped industrial balances. As it often occurs in technological trajectories, the pioneers in the initial stages weren’t necessarily the winners in the long run. Some companies that had invested in alternative or incompatible solutions were progressively marginalized, whereas new actors managed to seize the opportunities offered by an open standard and gain a competitive advantage.

For instance, the HomeRF consortium represents an emblematic example of failure. Formed by major companies such as Intel, Microsoft, and Hewlett-Packard, HomeRF sought to develop a wireless standard mainly addressed to the household environment. The technology was simpler than 802.11, but it offered inferior performance, with a maximum speed of only 1.6 Mbps. Despite the strong industrial support, it failed to establish itself. As explained by Negus and Petrick, “[...] because the competitive 10 Mb/s HomeRF products did not become commercially available until mid-2001, by the end of 2001 802.11b products took over the entire WLAN market.” (Negus and Petrick, 2009: 48)

The superior performance of 802.11b and the support from the Wi-Fi Alliance quickly rendered HomeRF obsolete.

The case of HomeRF demonstrates that, in the context of networking technologies, the support of major industrial players is not enough. What really matters is the ability to integrate into a broader ecosystem, reinforced by network effects and interoperability. Without these conditions, even consortia backed by leading firms can quickly find themselves left behind.

At the same time, the industrial landscape of the market winners also shifted. In the early phase, the leaders were equipment and systems manufacturers such as NCR, Symbol Proxim, and Aironet, which developed the first network cards and access points. Nevertheless, as standardization advanced and Wi-Fi began to spread globally, the center of gravity rapidly shifted towards the chipmakers. Companies like Broadcom, Atheros, Intel, Intersil, and Marvell succeeded in integrating Wi-Fi functionality directly into their chipsets. As a consequence, they were able to reduce production costs and make large-scale adoption possible. (Hayes and Lemstra 2009)

This shift marked a profound industrial transformation. Hardware producers that had dominated the pioneering stage progressively lost relevance, while semiconductor manufacturers acquired a central role in the value chain. Competitive advantage no longer derived from producing costly and specialized cards, but from the ability to shrink and integrate Wi-Fi connectivity directly into the core components of electronic devices.

The lesson that emerges is clear: in markets characterized by open standards and strong network effects, the companies that succeed are not necessarily the early entrants, but those that can bring the technology to scale and adapt it to mass demand. For instance, pioneers like NCR and Proxim played a central role in paving the way, but chipmakers were the ones to consolidate and capitalize on Wi-Fi's success.

In conclusion, the standardization process was not neutral: it determined winners and losers, shifting power from early movers to actors capable of exploiting economies of scale and entering a global standard. The failure of HomeRF and the success of chip producers show that Wi-Fi was not only a technological achievement but also a profound transformation of the industrial structure in the telecommunications sector.

2.6 Economic and Policy Implications

The story of Wi-Fi makes it clear how regulation and business strategies can work side by side in the spread of a new technology. With the FCC's 1985 decision to allow unlicensed use of the ISM bands, entry barriers dropped, and firms were suddenly able to test new solutions without paying for costly licenses. That decision did not determine in advance which technology would become dominant, but it opened the way for open standards and collaboration among firms to develop.

The way things developed was also different from what usually happens in the telecommunications sector. In mobile telephony, for example, innovation was tied to licensed spectrum and managed through international bodies, making it harder for new entrants to play a role. Wi-Fi instead grew under an open access regime, and this meant that both established firms and newcomers had the chance to compete.

Interoperability was another turning point. Thanks to the Wi-Fi Alliance, consumers could trust that devices from different brands would actually work together. For producers, this reduced the risks of investing, since their products would be part of a broader system. This shift helped turn Wi-Fi from a technical specification into a consumer label, and reinforced network effects: the more products on the market, the stronger the incentives for new users and new firms to adopt it.

Finally, the case also makes clear that regulation is never neutral. The FCC's light-touch approach encouraged variety and experimentation, but without the strategies of Apple with AirPort, Intel with Centrino, and the branding activities of the Wi-Fi Alliance, that regulatory move would not have been enough on its own. The broader point is that flexible regulation, combined with the capacity of firms to adapt, can lead to the spread of a technology far beyond what was originally expected.

2.7 Conclusion

As we argued above, the trajectory that turned Wi-Fi into a global infrastructure can be understood through a series of decisive moments that marked regulatory, technical, and industrial shifts. In 1985, the FCC's decision to open the unlicensed spectrum set the

institutional foundation for a new market. In 1997, the approval of the first IEEE 802.11 standard provided the technical framework needed to ensure interoperability and reliability. In 1999, the creation of the Wi-Fi Alliance and Apple's launch of AirPort transformed what was a technical specification into a recognizable product for consumers. Finally, in 2003, Intel's Centrino program consolidated Wi-Fi as the default option for laptops, which secured its global diffusion.

Despite being different in nature, these events all represent fundamental turning points in the evolution of Wi-Fi. Each of them influenced market conditions and created new opportunities for innovation. Regulation opened the initial space, the standard guaranteed compatibility, branding made the technology visible and appealing, and industrial strategies enabled large-scale adoption. Taken together, these factors have contributed to transforming Wi-Fi from a niche experiment to a widely diffused and essential infrastructure.

From an empirical point of view, these turning points are not only historical markers, but also real "shocks" that help us understand how innovation responded to changes in the environment. They are considered temporal benchmarks for testing whether patenting activity accelerated after important regulatory or industrial developments. The hypothesis is that these regulatory and industrial breaking points had a direct influence on innovation, both in terms of the number of patents and in the strategies of the firms involved.

The link between historical reconstruction and data analysis is fundamental. The events described in this chapter are not only the context but also the reference points that guide the empirical investigation. They clarify why certain moments are meaningful and how they might have shaped the incentives for firms to innovate.

In conclusion, Chapter 2 has shown how the history of Wi-Fi has been marked by the interaction of regulation, open standards, and industry strategies, which together created a diffusion process accelerated by network effects. Chapter 3 will now move from this historical overview to the empirical side. It introduces the dataset, the variables, and the methodology used to evaluate whether the turning points identified here had a measurable effect on patenting activity and on the evolution of innovation in the sector.

CHAPTER 3

DATASET AND DESCRIPTIVE STATISTICS

3.1 Dataset Description

The main dataset used in this thesis, *Wi-Fi_Patent_Dataset*, was sourced from the United States Patent and Trademark Office (USPTO).

The dataset is sector-specific since it focuses on patent activity specifically related to Wi-Fi and Wireless Local Area Network technologies (WLANs) across various domains. Specifically, it covers:

- Telecommunications and Networking.
- Consumer Electronics and Digital Entertainment.
- Semiconductors Electronic Components.
- IT, Software, and Cybersecurity.

The patent covers the innovative activity of firms active over a long period of time, from 1924 to 2020; therefore, it captures crucial milestones in Wi-Fi standardization:

- 1) The initial phase, with the introduction of the IEEE 802.11 standard in the late 1990s,
- 2) The expansion phase, marked by rapid adoption throughout the 2000s, and
- 3) The consolidation phase, where many large firms dominated in the 2010s and beyond.

The original dataset is organized at the patent level, meaning each entry corresponds to a distinct patent. In total, it includes 60,122 patents assigned to 209 unique assignees over 96 years.

Each patent in the dataset is accompanied by a set of identifiers. The key variables are:

- `Publication_Number`: Each patent is given a publication number once the application is disclosed by the patent office. This identifier is different from the filing number and from the grant number. It specifically marks the document that makes the invention visible to the public. It is often the most

practical way to detect patents across different databases.

- Title_(English): This is the title assigned to the patent, indicating its content and technological field of domain. In the dataset, it represents the first piece of information to identify the sector to which each patent belongs.
- Optimized_Assignee_patent: This field identifies the patent holder. Originally, patents may list different names: Assignee_Applicant_First (the first entity submitting the application, which could be the inventor himself or the company they work for), Optimized_Assignee or Company_Name, which correct minor inconsistencies. However, even with these adjustments, the same company may still appear under multiple variants or subsidiaries. To address this issue, the Optimized_Assignee_patent field is employed as the preferred option, as it consolidates the different name variations and group subsidiaries under a single entity. This ensures more accurate attribution of patents to firms and makes it easier to compare their innovative activity.
- Priority Date: This refers to the date of the first filing of an invention, establishing its legal protection. It is the legal starting point of the patent family and establishes precedence over any later applications for the same idea in other jurisdictions. In empirical research, this date is often used to approximate when the inventive activity originally took place. For instance, if an invention is first filed in the United States in 2018 and then submitted in Europe in 2019, the priority date remains the original 2018 filing. In the dataset, this date situates the origin of the innovation in time.
- Application Date: It corresponds to the day when a patent application is formally submitted to a patent office. It represents the moment at which the office begins to process the application in that jurisdiction. In this thesis, the application date is adopted as the main reference date in all the conducted analysis, since it provides a consistent benchmark across all patents included in the dataset.
- Publication Date: It marks when a patent application is disclosed to the public, which usually happens around eighteen months after filing. From this moment, the technical content of the invention is disclosed to other firms, researchers, and the wider community. In this dataset, this variable helps to analyze when inventions became publicly available and when technological spillovers could

begin.

- **IPC_Current:** Patents are classified using IPC codes (International Patent Classification), which assign each document to one or more areas of technology (for example, electronics, telecommunications). This variable makes it possible to group inventions by sector and to compare innovation dynamics across fields. In this thesis, IPC codes are used to identify the technological domains where Wi-Fi related patents are concentrated.
- **Citing_Patents** (forward citations): They represent the number of subsequent patents that explicitly cite a given invention. Generally, forward citations are used as an indicator of technological impact: highly cited patents are assumed to be influential, since later innovations build upon them, in the dataset, this variable is used to detect the most impactful patents in the evolution of Wi-Fi technologies.
- **Cited_Refs_patent** (backward citations): It refers to the patents that are cited within a new application. They represent the prior knowledge on which the invention relies. Backward citations, therefore, illustrate the technological roots of an innovation and are useful to trace how knowledge flows from older to newer patents.
- **Dead_Alive:** This field indicates whether the patent is still legally valid (alive) or has expired (dead). A patent typically becomes inactive when renewal fees are not paid or when the maximum protection period, which is typically twenty years, has expired.
- **Estimated_Expiration_Date:** It indicates when a patent is expected to lose protection. In most jurisdictions, patents have a standard duration, which is often twenty years from the filing date if renewal fees are paid regularly. The estimate, therefore, reflects the maximum potential duration, but in practice, some patents expire earlier if maintenance is discontinued.

3.2 Data Cleaning and Variable Construction

Before carrying out the descriptive and econometric analysis, some work was needed to prepare the dataset and ensure consistency and reliability. This process involved cleaning

the raw data and creating additional variables that would make the analysis more informative.

As a first step, we carefully checked the data for inconsistencies. In a few cases, the same patent appeared more than once, most likely because it was retrieved from different sources or extracted twice. These duplicates were removed so that each patent would only be counted once in the dataset. We also encountered several cases with missing values or incomplete entries, especially in the assignee names. These were corrected or, when the missing information could not be retrieved, the corresponding observations were excluded. These adjustments made the dataset more accurate and easier to interpret.

In addition to cleaning, we introduced a few additional variables to complement the original information:

- Main IPC Class and Code: Each patent was assigned to a main IPC class, allowing us to group inventions by their dominant technological field.
- H04W_present: A dummy variable indicating whether the patent included the IPC code H04W, as this class is particularly relevant for wireless communication networks and therefore central to Wi-Fi-related innovation.
- Number of citing patents: This is the number of future patents citing a given invention. This forward-looking measure helps identify the most influential inventions.
- Number of cited patents: The number of prior patents cited by each application. These backward citations represent the knowledge base behind each invention.

Alongside patent-level adjustments, assignees were also classified according to organizational type. Based on available information, companies were grouped into four categories:

- Independent: Companies that operate autonomously, without being part of a larger corporate group.
- Spinouts: New firms that originate from existing organizations, such as corporations or research institutions. They are often set up to commercialize a specific technology.
- Subsidiaries: Firms owned or controlled by larger corporations, which may use them to manage specific technological portfolios or regional activities.

- Joint ventures. Firms established as collaborative initiatives between two or more parent companies, usually to share risks and resources in technology development.

This classification was included when rearranging the dataset at the firm level. Although this information is not directly used in the econometric modelling, it provides useful context in the descriptive analysis, as it highlights the types of organizations that are most active in Wi-Fi patenting.

After these steps, the dataset became more coherent and informative. The cleaning process ensured that each observation was reliable, while the new variables and firm classification provided a richer foundation for the descriptive statistics presented in Section 3.3.

3.3 Descriptive Statistics

To better understand how innovations related to Wi-Fi standardization have evolved over time, we first present some descriptive analysis conducted on our raw dataset. This section gives a general overview of the patents' evolution over time, the characteristics of the assignee companies, with particular attention to their entry-exit dynamics and their life duration, and finally the innovative impact of the patents assessed through the analysis of their citation patterns.

3.3.1 Patent Activity Over Time

Our dataset covers a long-time span, from 1924 to 2020, making it challenging to conduct our analysis in a comprehensive and meaningful way. We observed that the number of patents from 1920 to 1980 was very low compared to the subsequent decades. Because of such observations, we decided to study the temporal evolution of patent activity by grouping all years prior to 1980 into a single category and organizing the following years into five-year intervals. As shown in Table 3.1, this approach results in nine different periods, each associated with the respective number of patents.

Table 3.1 – Number of Patents by Period

Time-Period	Number of Patents
< 1980	173
1980-1984	70
1985-1989	271
1990-1994	767
1995-1999	2011
2000-2004	4243
2005-2009	8286
2010-2014	19486
2015-2020	24815
Total	60122

As shown in Figure 3.1, patent activity over time appears highly dynamic and growing over time, with peaks in correspondence of meaningful events related to Wi-Fi standardization, such as normative shocks or influential technological changes, followed by periods of consolidation. This evidence shows that the sector is strongly reactive to external events, and particularly sensitive to reforms and innovations in wireless communication standards. For instance, the first meaningful increase in patenting is registered between the 1995-1999 and 2000-2004 periods, revealing the positive impact of the introduction of the IEEE 802.11 Standard in 1997.

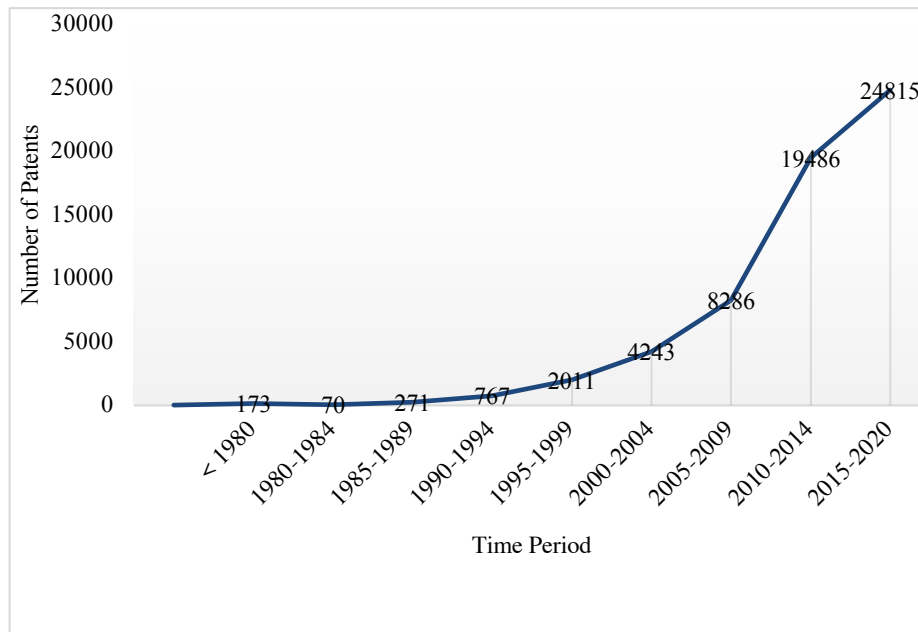


Figure 3.1 – Evolution of Wi-Fi Patents Over Time (1924 – 2020)

3.3.2 Patent Technological Distribution (IPC)

To better understand the nature of patenting activity connected to Wi-Fi development we have to consider the technological dimension, which can be analyzed through the International Patent Classification (IPC) codes associated with each patent. IPC classes allow us to recognize the technological field that refers to every invention, and the average number of IPC classes per patent can be interpreted as an indicator of its complexity and multi-disciplinarity.

As shown in Figure 3.2, until the 1990s, patents presented on average a limited number of IPC classes, between 2.7 and 3.9. This observation reflects an initial phase in which inventions related to Wi-Fi were mainly confined within restricted technological domains.

From the second half of the 1990s, and particularly in the period 2000-2004, we observe a sharp increase, with an average value of more than 6 IPC classes per patent. The pattern we observe indicates a phase of strong technological convergence, during which innovations were no longer confined to basic telecommunications, but they increasingly incorporated contributions coming from heterogeneous sectors such as consumer electronics, wireless security, and digital transmission systems.

In the following years, the average IPC number dropped drastically, reaching values between 4.5 and 5, but it rose again in the last period of observation (2015-2020), when it

reached the value of nearly 6. This recent increase may be interpreted as evidence of a new expansion of Wi-Fi-related technological applications, mainly driven by integration with emerging fields such as the Internet of Things and smart devices.

Overall, the evolution of the average number of IPC classes shows that the development of Wi-Fi technology has led to both an increase in the number of class and a widening of the variety, characterized by a progressive increase in its technological heterogeneity and by its ability to generate innovation across multiple sectors.

Table 3.2 – Average of Number of IPC Classes by Period

Application Period	Average of Number of IPC Classes
< 1980	2.673469388
1980-1984	3.142857143
1985-1989	3.520295203
1990-1994	3.907431551
1995-1999	4.863252113
2000-2004	6.814282347
2005-2009	4.954018827
2010-2014	4.571025352
2015-2020	5.956155551
Grand Total	5.342121021

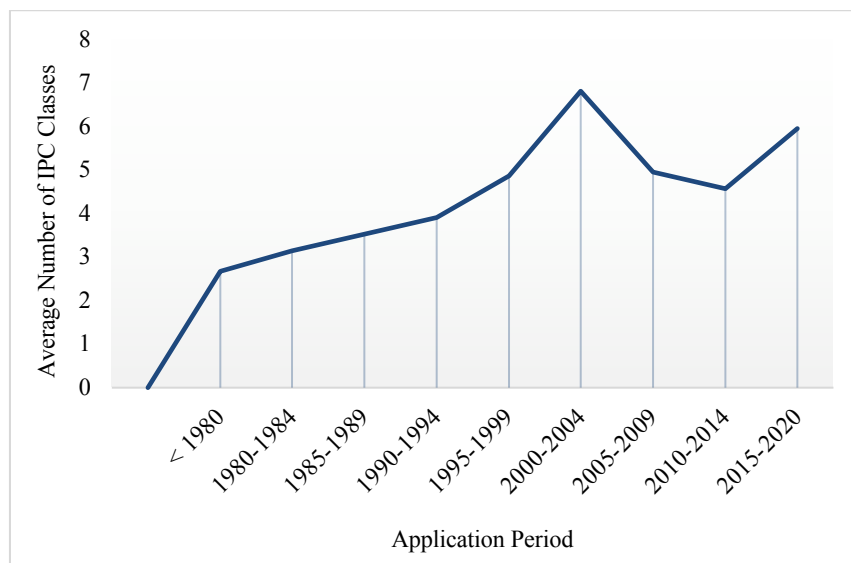


Figure 3.2 – Distribution of Average Number of IPC Classes by Period

Further evidence concerns the distribution of patents by their main IPC technological class. As reported by Table 3.3, which indicates the number of patents of the top 10 IPC classes, most patents are concentrated in section H04W, Wireless Communication Networks, which gathers innovative activities related to the management and control of wireless networks. Inside this section, the sub-class H04W000400 stands out, and it refers to signaling and handover procedures in mobile networks, accounting for more than 6,400 patents.

Other than this central grouping, other relevant groups are found in H04B, Transmission Systems, which regards innovations related to radio signal transmission, and H04L, Transmission of Digital Information, which includes protocols and digital data management.

This distribution confirms that the development of Wi-Fi technology does not regard only one technical domain, but it was born from the convergence of several fields, which span from wireless communication networks to signal transmission and digital data management.

Table 3.3 – Number of Patents by Main IPC Class

IPC Class	Number of Patents
H04W000400	6493
H04W007204	3382
H04B000700	1642
H04W000400	1490
H04W003600	1347
H04L000500	1334
H04W002400	1239
H04L001228	1077
H04L002906	1010
H04W007200	925

3.3.3 Entry – Exit Dynamics of Firms

In parallel, the analysis of the companies that operate in the sector reveals high mobility. Figure 3.3 shows that every year a consistent flux of new entrants is registered in the patenting market. Nevertheless, only a small portion of them can survive in the long run, as confirmed by the evidence reported in Figure 3.4 (Company Life Duration).

The combination of such results suggests that the sector is characterized by a strong dynamic of natural selection: many firms enter the market, driven by the opportunities offered by Wi-Fi technology, but only few of them can consolidate and maintain a stable role over time.

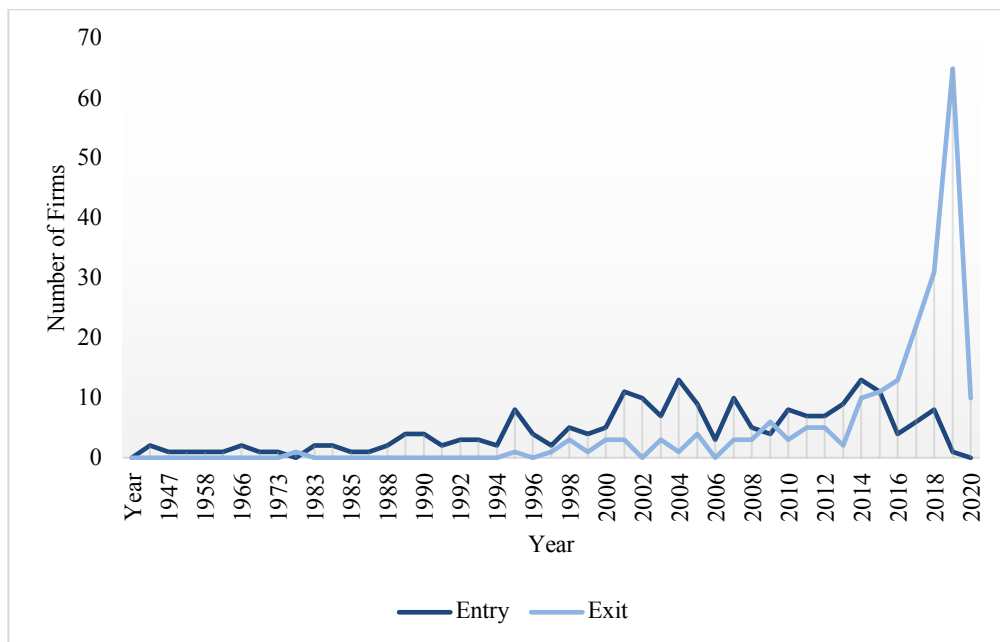


Figure 3.3 – Entry and Exit of Firms in the Patent Market

As shown in Figure 3.3, until the mid-1990s the number of new entrants in patenting was marginal, reflecting the pioneering phase of Wi-Fi when the technology was not standardized nor diffused yet.

After 2000, entries surge more steadily with a remarkable peak in 2015-2018, likely driven by the development of related markets, such as the Internet of Things, smart devices, 5G and technologies of advanced connection, that pushed new operators to patent in the sector.

Despite the peak of new entries, the number of exits increases, too, especially in the following years, confirming that most operators cannot survive for a long time, suggesting the natural selection mechanism: while many firms attempted to enter, only a few were able to consolidate their presence in the market, while incumbents maintained their dominant position.

The complete list of the number entries and exits per year of observation is reported in Appendix B (Table B.1).

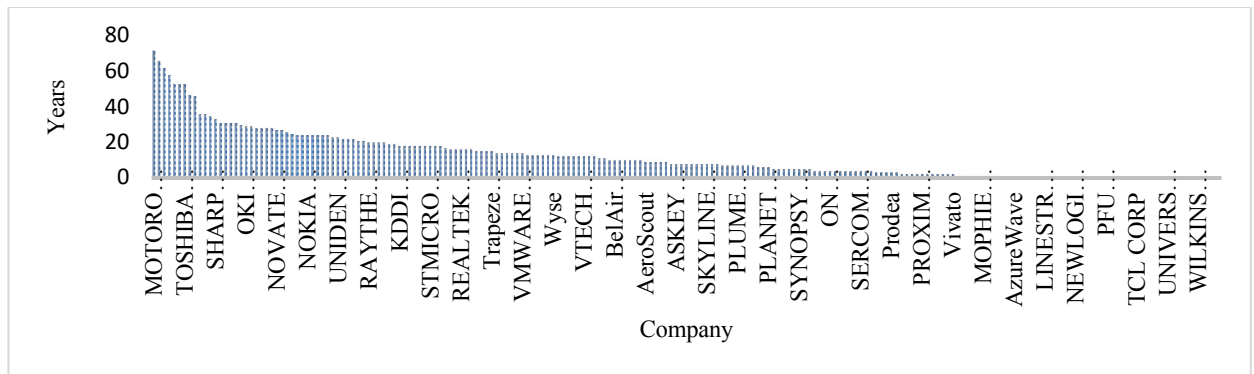


Figure 3.4 – Company Life Duration

Figure 3.4 shows the distribution of companies' life duration, measured as the duration of their patenting activity in the Wi-Fi sector. Such distribution appears quite heterogeneous since only few historical incumbents, such as Motorola, Verizon, NEC, Samsung, and Qualcomm, register a long-term presence, often more than decades, thanks to continuous investments in research and development and their strong ability to adapt to technological shocks.

Most firms show a much shorter presence, of about less than ten years, resulting in a very skewed distribution: on the one hand, there are few actors that have been maintaining a dominant role for a long time; on the other, a mass of new entrants that cannot consolidate their presence and consequently rapidly abandon the market.

Such evidence is coherent with the natural selection pattern: only firms with adequate resources and efficient innovative strategies succeed in surviving over a long time, while most of the operators are confined to a temporary presence in the market.

3.3.4 Patent Concentration

The analysis of concentration indices shows a clear dynamic of market evolution. Up to the 1980s, patenting activity was almost entirely dominated by a small group of assignees. During the 1990s, concentration drastically decreases because of the Wi-Fi standardization process and the entry of new operators. From the 2000s onwards, concentration stabilized at lower levels: a few incumbents continued to maintain dominance, but in a context characterized by higher competition and by a broader distribution of the innovative activity.

Table 3.4 and Figure 3.5 report the distribution of the concentration index of Herfindahl-Hirschman (HHI)¹ over time. Before 1980, the HHI was at 0.33, and then peaked at 0.60 in 1980-1984, reflecting a market dominated by just a few players. In the following years, concentration fell rapidly: the index dropped to 0.24 in 1990-1994 and reached its minimum value of 0.07 in 1995-1999. After 2000, the decline stopped and the HHI settled within the range of 0.09-0.12. This stability suggests that new firms entered the market and, thus, competition increased.

Table 3.4 – HHI Over Time

Period	HHI	Level of Concentration
< 1980	0.3329	High
1980-1984	0.6086	Very High
1985-1989	0.5113	Very High
1990-1994	0.2404	Moderate (borderline)
1995-1999	0.0742	Low
2000-2004	0.0969	Low
2005-2009	0.1229	Low
2010-2014	0.1113	Low
2015-2020	0.0981	Low

¹ The HHI is computed on the top 10 assignees of each subperiod.

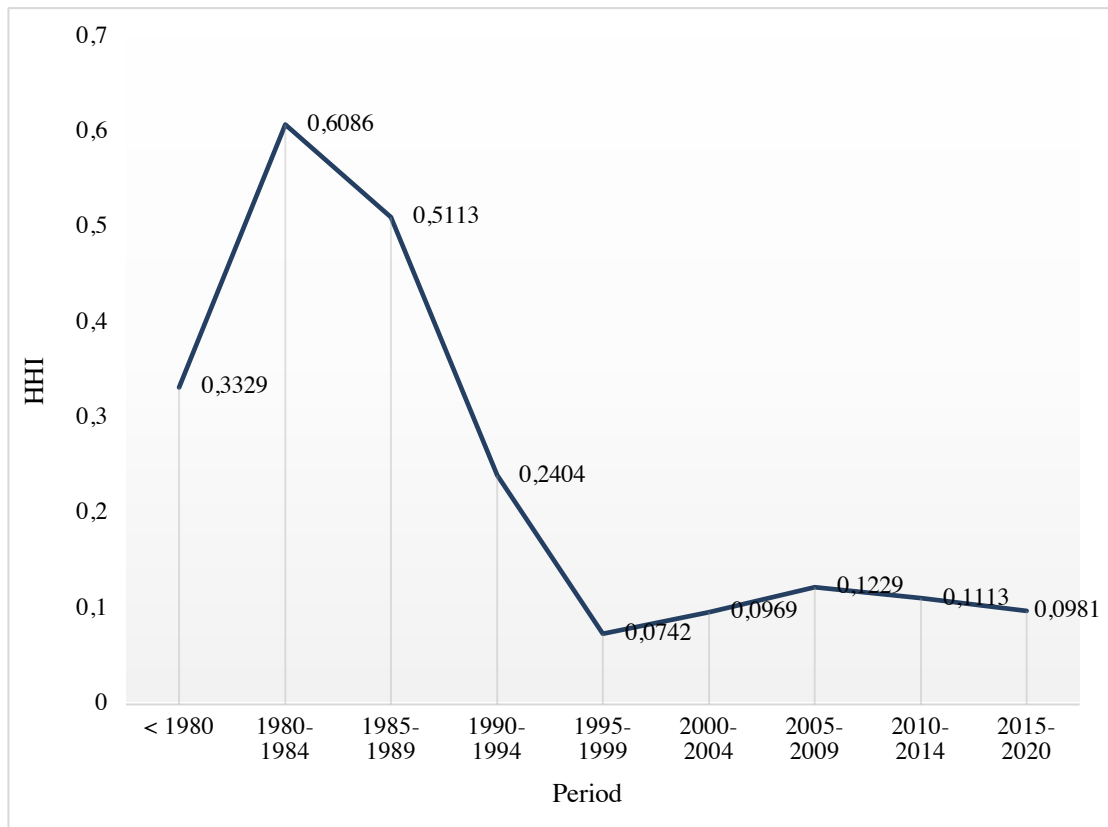


Figure 3.5 – Distribution of HHI Over Time

The same pattern is confirmed by the Four-firm Concentration Ratio (CR4).² Table 3.5 and Figure 3.6 show that sector was highly concentrated until the 1980s: during 1980-1984 the CR4 reaches the maximum value of 0.97, showing that the four main operators controlled almost the entire patenting activity.

In the 1990s a sharp reduction in concentration is observed, with CR4 decreasing to 0.67 in 1990-1994 and reaching its minimum of 0.45 in 1995-1999. This drop reflects the entry of many new players that were attracted by the opportunities generated by the Wi-Fi standardization and the increasing diffusion of wireless technologies.

From 2000s onwards, the concentration rises slightly and stabilizes around 0.50-0.60, indicating that the market remains dominated by few main actors that can maintain a leading role over time, even in the presence of broader competition.

² The CR4 index represents the share of patents held by the top 4 assignees in each subperiod.

Table 3.5 - CR4 Over Time

Period	CR4
< 1980	0.8504
1980-1984	0.9715
1985-1989	0.893
1990-1994	0.6728
1995-1999	0.4526
2000-2004	0.5124
2005-2009	0.6124
2010-2014	0.6062
2015-2020	0.6002

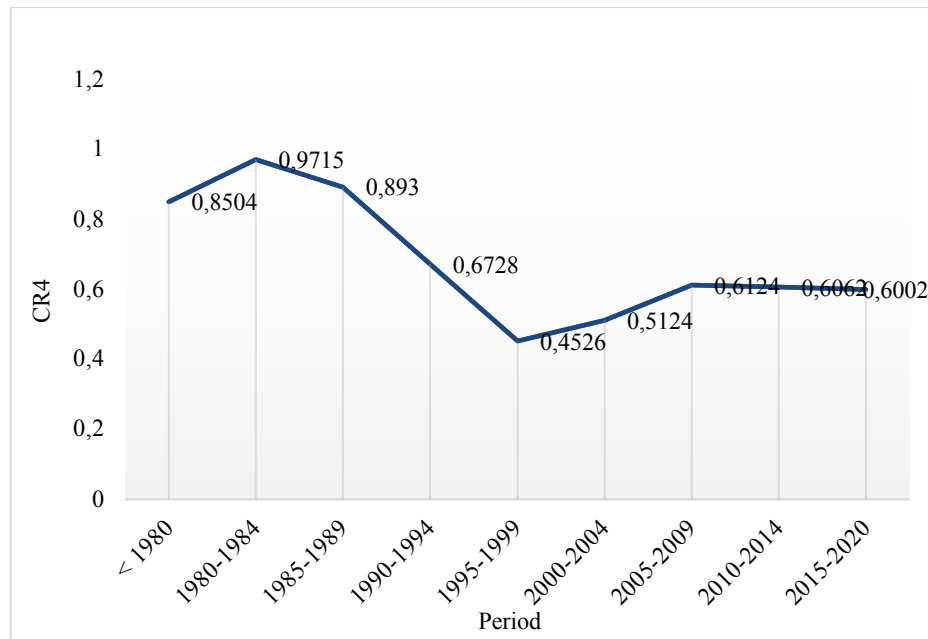


Figure 3.6 – Distribution of CR4 Over Time

3.3.5 Ranking Over Time

The dynamics highlighted by the concentration indices are confirmed by the ranking of assignees over time. As we can see from table 3.6, the evolution of the top ten positions among patent holders shows a strong persistence: a few incumbents, such as Motorola, Samsung, Qualcomm, and NEC, consistently maintain leading positions, while new entrants

rarely manage to challenge these consolidated leaders. For example, Motorola dominates until the late 1990s, gradually ceding its leading position to Qualcomm, which leads throughout the early 2000s. In the period 2015-2020, leadership shifts to Samsung, while Qualcomm and Huawei increasingly play a relevant role.

This evidence confirms the idea of a polarized market, where leadership remains concentrated in the hands of a few players despite the continuous entry of new firms.

New operators tend to temporarily hold a leading position in specific subperiods, but this trend does not end up challenging the dominance of incumbents.

Table 3.6 – Top 10 Firm Ranking by Period

	< 1980	1980-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2020
1	MOTOROLA SOLUTIONS INC.	MOTOROLA SOLUTIONS INC.	MOTOROLA SOLUTIONS INC.	MOTOROLA SOLUTIONS INC.	QUALCOMM INC.	QUALCOMM INC.	QUALCOMM INC.	QUALCOMM INC.	SAMSUNG ELECTRONICS CO LTD
2	RCA	Philips	Philips	MOTOROLA MOBILITY HOLDINGS INC	SAMSUNG ELECTRONICS CO LTD	SAMSUNG ELECTRONICS CO LTD	SAMSUNG ELECTRONICS CO LTD	LG ELECTRONICS INC.	LG ELECTRONICS INC.
3	Philips	OLYMPUS CORP.	MITSUBISHI ELECTRIC CORP	TOSHIBA CORP	MOTOROLA SOLUTIONS INC.	NOKIA CORP	LG ELECTRONICS INC.	SAMSUNG ELECTRONICS CO LTD	HUAWEI TECHNOLOGIES CO., LTD.
4	TEXAS INSTRUMENTS INC	UNIDEN CORPORATION	TOSHIBA CORP	QUALCOMM INC	NOKIA CORP	LG ELECTRONICS INC.	SPRINT CORP.	HUAWEI TECHNOLOGIES CO., LTD.	QUALCOMM INC
5	VERIZON COMMUNICATIONS INC	LG ELECTRONICS INC.	SONY CORP	PANASONIC CORPORATION	SONY CORP	SONY CORP	SONY CORP	SPRINT CORP.	SONY CORP
6	MITSUBISHI ELECTRIC CORP	NEC ELECTRONICS CORPORATION	VERIZON COMMUNICATIONS INC	Philips	PANASONIC CORPORATION	PANASONIC CORPORATION	HUAWEI TECHNOLOGIES CO., LTD.	ZTE MICROELECTRONICS TECHNOLOGY CORP.	ZTE MICROELECTRONICS TECHNOLOGY CORP.
7	TOSHIBA CORP		SHARP CORP	VERIZON COMMUNICATIONS INC	VERIZON COMMUNICATIONS INC	SPRINT CORP.	PANASONIC CORPORATION	SONY CORP	SPRINT CORP.
8	PANASONIC CORPORATION		OKI ELECTRIC INDUSTRY CO. LTD.	NOKIA CORP	Philips	MOTOROLA SOLUTIONS INC.	TOSHIBA CORP	VERIZON COMMUNICATIONS INC	VERIZON COMMUNICATIONS INC
9	YAMAHA CORP		SUMITOMO ELECTRIC INDUSTRIES LTD.	MITSUBISHI ELECTRIC CORP	MICROSOFT MOBILE	TOSHIBA CORP	MOTOROLA SOLUTIONS INC.	SHARP CORP	SHARP CORP
10			QUALCOMM INC	SONY CORP	TOSHIBA CORP	Philips	MITSUBISHI ELECTRIC CORP	PANASONIC CORPORATION	PANASONIC CORPORATION

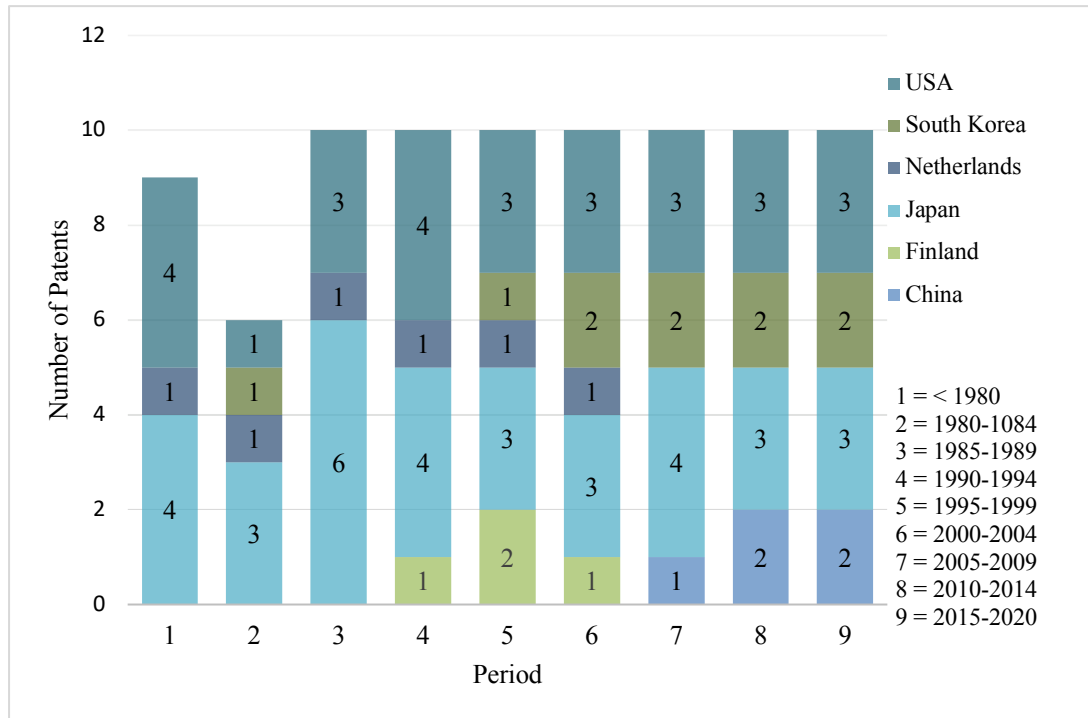


Figure 3.7 – Top 10 Assignee Companies Geographic Distribution

Figure 3.7 shows the distribution of the geographic location of leading patent holders which appears to be highly concentrated in few countries. During the early periods, the United States and Japan dominated patenting activity and maintained leadership until the 1990s. During the following years, South Korea entered the market with Samsung as its main leader, while China emerged as a new technological player, mainly after 2010.

Europe plays a more marginal role, with the occasional presence of companies such as Philips (Netherlands) and Nokia (Finland), which, however, could not maintain a stable position over time.

Overall, the geographic distribution of patent assignees confirms a persistent polarization, meaning that few global technological poles concentrate the innovative activity related to Wi-Fi, reflecting the asymmetric and geographically selective nature of this process.

3.3.6 Citations and Innovative Impact

Besides the number of patents, it is crucial to analyze their innovative impact, which can be assessed through the citations they have received. In economic literature and innovation studies, patent citations represent a widely accepted indicator of the technological relevance of an invention, as they reflect its contribution to the development of the subsequent patents and the diffusion of knowledge.

Citations analysis allows us to distinguish between a mere patenting activity and a real ability to influence the technological innovation. In particular, the purpose is to verify whether quantitative leadership also translates into qualitative leadership, thus reinforcing incumbent's predominance, or whether new entrants have been able to produce particularly influential innovations.

To capture this dimension more precisely, we computed the average number of citations per patent for each assignee company. Since absolute counts of cited or citing patents can be misleading, given that a single patent may receive or make multiple citations, the variables were normalized by dividing the total number of citations (received or made) by the total number of patents held by each company. This approach highlights the intensity of knowledge flows per patent, rather than the mere scale of patenting activity. A value greater than one indicates that, on average, each patent of the company received (or made) more than one citation.

Both cited (citations received) and citing (citations made) indicators were considered, as they capture complementary aspects of technological impact: cited patents reflect the influence of a company's inventions on subsequent developments, while citing patents indicate the extent to which a firm builds upon existing knowledge.

Figure 3.8 reports the results for the top 20 assignee companies, ordered by their average number of citations received per patent. The restriction to the top 20 was made for readability reasons. The results show that firms such as *Motorola Mobility Holdings Inc.* and *Qualcomm Inc.* stand out with particularly high averages of citations received per patent, suggesting their central role in shaping the Wi-Fi technological trajectory. Other players, including *Nokia Corp.*, *Philips*, and *Samsung Electronics Co. Ltd.*, also record high averages, confirming their relevance as both sources and users of Wi-Fi-related innovations.

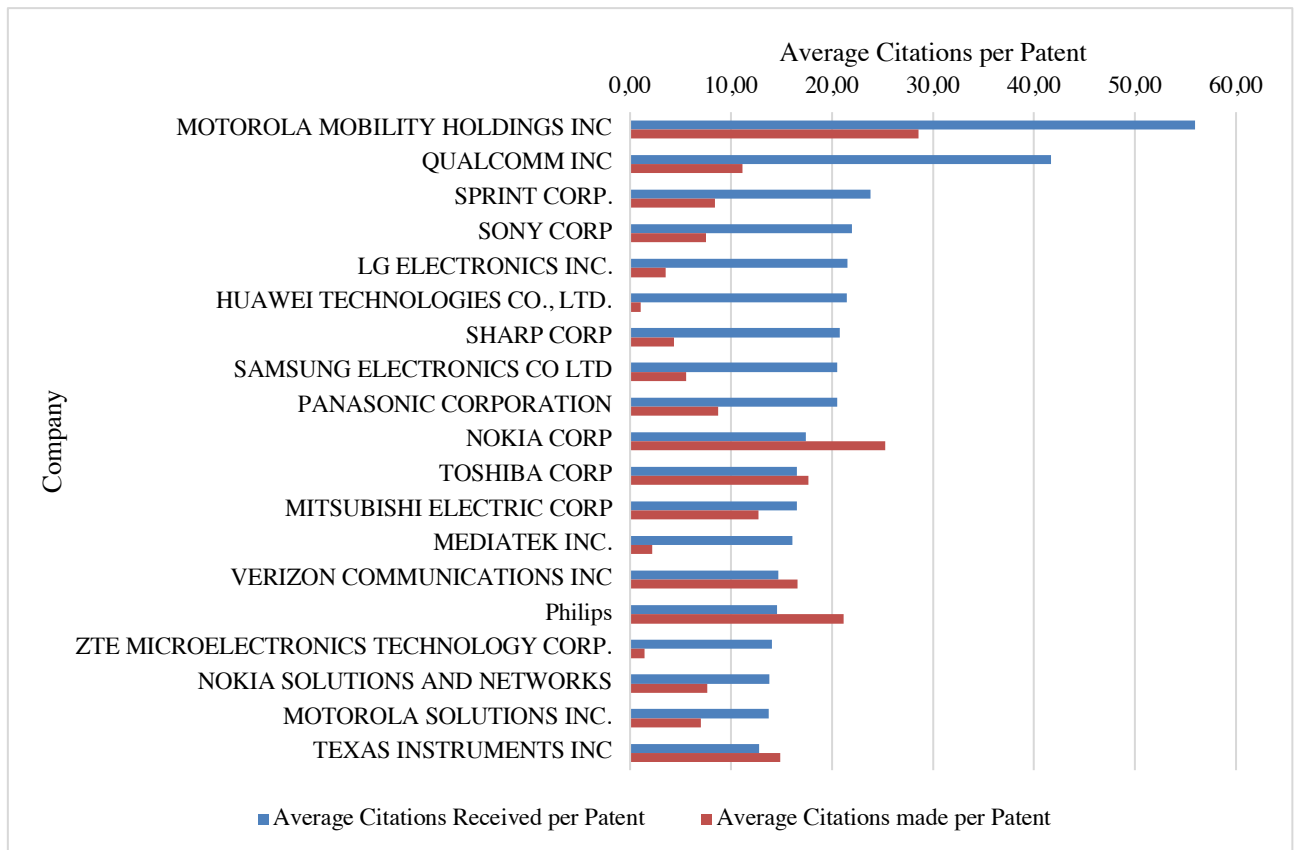


Figure 3.8 – Average Citations per Patent (received vs. made) for the Top 20 Assignee Companies

Tables 3.7 and 3.8 show the temporal evolution of cited and citing patents, where we observe two complementary dynamics. On the one hand, the number of cited patents increases exponentially in the last twenty years, ranging from negligible values before the 1990s to over 600,000 citations in period 2015-2020. This trend reflects the fact that patents related to Wi-Fi have progressively become a reference point for the development of new technologies, assuming a fundamental role in the diffusion of knowledge.

On the other hand, citing patents show a different pattern: their number rises until it reaches the maximum between the end of the 1990s and the beginning of the 2000s (more than 140,000 citations in periods 1995-1999 and 2000-2004), and then it drastically drops in the following decades, until it reaches less than 14,000 citations in period 2015-2020. Such reduction reveals the transition from an experimental phase of rapid expansion, characterized by a high utilization of prior knowledge, to a phase of technological maturity, in which Wi-Fi standard was consolidated and new inventions have progressively reduced the need of citing previous patents.

Overall, this evidence confirms how the sector transitioned from a phase of strong innovative dynamism and knowledge accumulation to a phase of consolidation, during which few historical patents remain the main technological reference for the entire sector.

Table 3.7 – Distribution of Cited Patents Over Time

Sum of Number of Citing Patents	
< 1980	3029
1980-1984	5155
1985-1989	28634
1990-1994	77051
1995-1999	141588
2000-2004	141255
2005-2009	73550
2010-2014	55411
2015-2020	13901
Grand Total	539574

Table 3.8 – Distribution of Citing Patents Over Time

Sum of Number of Citing Patents	
< 1980	3029
1980-1984	5155
1985-1989	28634
1990-1994	77051
1995-1999	141588
2000-2004	141255
2005-2009	73550
2010-2014	55411
2015-2020	13901
Grand Total	539574

3.3.7 Summary and conclusions of the descriptive analysis

The descriptive analysis of the patenting dataset related to Wi-Fi allowed us to outline several key patterns related to the technological and competitive development of the sector.

From the temporal point of view, data highlights a very dynamic context. After an initial marginal phase until the 1980s, we observe a steady growth in patent applications, with significant peaks coinciding with crucial events such as the introduction of the IEEE 802.11 standard in 1997 and the following spread of connected devices. This pattern reflects the sector sensitivity to technological and normative shocks, followed by phases of consolidation.

From the technological point of view, the analysis of IPC classes shows a progressive increase in the complexity of inventions. In period 2000-2004, the average number of IPC classes per patent reaches high values (telecommunications, electronics, connection security, data transmission). In recent years, such complexity has broadened, also thanks to the Wi-Fi integration with emerging fields such as the Internet of Things and smart devices.

From the point of view of companies, evidence shows strong turnover. Even though the number of new entrants is significant in each period, only a small portion can survive in the long run. Most firms, in fact, have a very short patenting life, confirming the dynamic of natural selection which rewards the most solid and innovative players.

The analysis of concentration (HHI and CR4) provides further insights. Initially, few actors controlled almost entirely the patenting activity, then, during the 1990s, the entrance of new players reduced concentration. However, from 2000 onwards, we observe higher stability, with few incumbents maintaining leadership. This dynamic is confirmed by the ranking of assignees, which highlights a strong persistence in the leading positions held by Motorola, Qualcomm, Samsung and, more recently, Huawei.

From the qualitative point of view, citations analysis marks an even stronger polarization. The most influential and the most cited patents belong to few firms, in particular Qualcomm and Motorola. The same pattern is observed when analyzing citing patents, since few firms (Qualcomm, Verizon, Philips, and Mitsubishi Electric) concentrate most of citations, demonstrating their capacity of integrating and making the most of prior knowledge.

Finally, geographical distribution confirms the concentration of innovative activity in few locations: initially the United States and Japan, followed by South Korea (with Samsung) and, in the most recent years, by China (with Huawei). Europe, instead, shows a

more marginal role, and it is mainly represented by Philips and Nokia during some periods, but without the ability to permanently maintain a leading position.

CHAPTER 4

ECONOMETRIC ANALYSIS

4.1 Introduction

This chapter moves beyond the descriptive evidence presented in Chapter 3 and develops a set of econometric analyses designed to investigate the determinants and consequences of patenting activity in the Wi-Fi domain. The overall aim is to provide an empirical assessment of how firms have engaged with the technological trajectory shaped by Wi-Fi standardization, and whether such engagement has translated into differences in economic performance and survival.

The chapter addresses three main research questions:

First, which firm-level characteristics explain the propensity to patent and the ability to produce more highly cited patents? Second, do firms that patent more intensively also display superior economic performance, in particular in terms of revenues? Third, which firm-level factors observed at the time of entry influence the probability of survival in the years following the first Wi-Fi-related patent?

To answer these questions, three complementary econometric strategies are employed:

- (i) Count data models (Poisson and Negative Binomial) are used to estimate the determinants of patenting and citation activity.
- (ii) Panel regressions with firm and time fixed effects are implemented to assess the relationship between patenting and firm performance, proxied by revenues.
- (iii) Survival analysis models, including the Cox proportional hazards model, Weibull specifications, and discrete-time complementary log-log models, are used to investigate the determinants of firm exit.

4.2 Datasets and Variables

The econometric analysis is based on a set of datasets obtained from the original patent database, each tailored to a specific empirical objective:

1. *Info_Company_CrossSection*

This file contains one observation per firm, where firm names have been consolidated in order to avoid multiple counting of subsidiaries or brand names belonging to the same corporate group. The dataset reports aggregated patent-related variables, such as the total number of patents, forward and backward citations, entry and exit years, the main IPC code, the weighted average number of inventors and assignees, as well as the firm's location and sector. This dataset is employed in the cross-sectional analysis of the determinants of patenting activity, estimated with count data models.

2. *Compustat_Panel_Def*

This dataset provides annual balance sheet information for a sub-sample of 68 firms. It is structured as a firm-year panel and includes financial variables from *Compustat* such as revenues, number of employees, R&D expenditures, and net income. Variables were standardized to consistent units, and a set of derived measures was created, including natural logarithms of the main variables, R&D intensity (in original, winsorized, and capped versions), and year-over-year growth rates.

3. *Merged_68_Panel*

By merging patent information with the *Compustat* panel, a combined dataset was constructed where each observation corresponds to a firm-year. This integrated dataset enables the econometric investigation of the relationship between patenting activity and firm performance, allowing for the inclusion of both innovation-related and financial covariates.

4. *Survival_Panel*

Finally, for the survival analysis, a firm-level dataset was assembled for the 39 firms with complete data. Each observation reports the year of first Wi-Fi-related patent (*entry year*), the year of exit or right-censoring (*exit year*), the spell length, an event indicator (1 if exit is observed, 0 if censored), and firm-level covariates measured at entry (revenues, R&D expenditures, employees, and R&D intensity).

In summary, the empirical strategy relies on three complementary data structures: a cross-sectional dataset for the analysis of patent determinants, a firm–year panel for the study of the relationship between patenting and performance, and a survival dataset for the estimation of firm exit hazards. Outcomes of interest include: the number of patents, forward citations, revenues, and survival duration, while covariates capture firm size, R&D investment, R&D intensity, inventive activity, and sectoral affiliation.

4.3 Econometric Method

This section outlines the econometric approaches used to address the three research questions of the thesis: the determinants of patenting activity, the relationship between patenting and firm performance, and the survival of firms active in Wi-Fi–related innovation. Each question requires a distinct modelling framework: (i) count data models, (ii) panel regressions, and (iii) survival models. The common rationale is to choose econometric tools consistent with the data structure and the statistical properties of the dependent variables.

4.3.1 Count Data Models

Patent and citation counts are discrete, non-negative variables often characterized by skewness and overdispersion, with a majority of firms producing few patents and a small number of firms producing a very large share. Ordinary least squares (OLS) is therefore not appropriate, as it assumes normally distributed errors and can predict negative values. Count data models explicitly account for the distributional properties of non-negative integers.

The *Poisson model* assumes that the dependent variable y_i (number of patents or citations for firm i) follows a Poisson distribution with conditional mean μ_i :

$$\Pr (y_i = \kappa | X_i = \frac{\mu_i^\kappa e^{-\mu_i}}{\kappa!}, \mu_i = \exp(X_i \beta + \ln exposure_i), \quad (1)$$

where X_i are firm-level covariates and $\ln exposure_i$ is an offset accounting for differences in years of observation (e.g., years active).

The key assumption of the Poisson model is equidispersion: the conditional variance equals the conditional mean ($\text{Var}(y_i|X_i)=\mu_i$). This is often violated in patent data, which almost invariably display overdispersion, where the variance substantially exceeds the mean.

The *Negative Binomial (NB) model* relaxes this assumption by introducing an overdispersion parameter α :

$\text{Var}(y_i|X_i) = \mu_i + \alpha\mu_i^2$, $\alpha > 0$. A significantly positive α indicates that the Negative Binomial specification provides a better fit to the data. When $\alpha=0$, the NB collapses to the Poisson.

Coefficients are interpreted via Incidence Rate Ratios (IRRs), which facilitate interpretation:

$$\text{IRR} = e^{\beta_j} \tag{2}$$

For example, an IRR of 1.10 for the average number of inventors implies that a one-unit increase in inventors is associated with a 10% increase in the expected patent rate, holding other covariates constant. This interpretation is standard in the literature on patent econometrics (Hausman et al. 1984). A comprehensive methodological treatment of count data models can be found in Cameron and Trivedi (2013).

4.3.2 Panel Regressions

Having established the determinants of patenting, the analysis then turns to firm performance. Firms' performance varies over time, suggesting the use of panel regressions to exploit both the cross-sectional and temporal dimensions of the data.

To examine the relationship between patenting activity and firm performance, we employ a panel dataset that combines patent information with financial data. The dependent variable is the natural logarithm of firm revenues, while the main explanatory variable is patenting activity, measured either in levels or using logarithmic transformations. Additional firm-level controls include employment and R&D expenditures, both expressed in natural logs.

The general specification is:

$$\ln(\text{Revenues}_{it}) = \gamma \cdot f(\text{Patents}_{i,t-k}) + \theta \ln(\text{Employees}_{it}) + \phi \ln(\text{R\&D}_{it}) + \mu_i + \tau_t + \epsilon_{it},$$

where i indexes firms, t years, and k a potential lag to capture delayed effects of innovation. The term μ_i denotes firm fixed effects, which absorb time-invariant unobserved heterogeneity (such as managerial quality or long-run strategies), while τ_t represents year fixed effects, capturing common shocks such as industry-wide technological shifts or macroeconomic crises.

The use of panel regressions is motivated by the need to control for unobserved heterogeneity that may otherwise bias the estimates (Wooldridge 2010). In particular, fixed effects models are preferable when firm-specific unobservables are correlated with the regressors, while random effects models do not assume such correlation.

The log transformation of revenues and other firm size variables allows coefficients to be interpreted as elasticities. For example, if $\gamma = 0.05$, this implies that a 1% increase in patents is associated with a 0.05% increase in revenues, *ceteris paribus*.

Additional robustness checks are performed to verify the stability of the results.

4.3.3 Survival Models

Beyond performance, a final set of models addresses firm survival after entry into Wi-Fi patenting.

To analyze firms' survival after entering Wi-Fi-related patenting, we estimate models where the event of interest is the exit of the firm from the financial dataset. Duration is measured as the number of years between the first Wi-Fi patent (*entry year*) and the last observed year in *Compustat* (*exit year*). If the firm is still present at the end of the panel, the observation is treated as right-censored.

The empirical strategy begins with a non-parametric description using the *Kaplan–Meier estimator* (Kaplan and Meier, 1958), which provides survival functions without imposing parametric assumptions on the baseline hazard:

$$\widehat{S}(t) = \prod_{j:t_j \leq t} \left(1 - \frac{d_j}{n_j}\right), \quad (3)$$

where t_j indexes distinct failure times, d_j is the number of exits at t_j , and n_j is the risk set just prior to t_j .

Kaplan–Meier curves allow a visual comparison of survival across entry cohorts or terciles of initial characteristics such as revenues, R&D expenditures, and employment. While this approach is informative, it does not allow for the joint inclusion of multiple covariates.

To address this limitation, the *Cox proportional hazards model* (Cox 1972) is employed. The Cox model specifies the hazard rate as

$$h(t|X_i) = h_0(t) \exp(\beta' X_i), \quad (4)$$

where $h_0(t)$ is an unspecified baseline hazard and X_i is a vector of firm-level covariates. The estimated coefficients are interpreted as hazard ratios (HRs): values greater than one indicate that the covariate increases the probability of exit, while values lower than one indicate longer survival. Robust standard errors clustered at the firm level are used to account for heteroskedasticity and serial correlation.

As a parametric robustness check, we estimate a *Weibull proportional hazards model* (Kiefer 1988), which assumes a monotonic baseline hazard:

$$h(t|X_i) = p\lambda t^{p-1} \exp(\beta X_i), \quad (5)$$

where p is the shape parameter and λ is a scale parameter. The interpretation of coefficients is identical to the Cox model, but the Weibull model also provides information about the time dependence of the hazard. If $p > 1$, the risk of exit increases with time; if $p < 1$, the risk decreases, implying that early failures dominate while survivors become more resilient over time.

Comparing Cox and Weibull results makes it possible to verify that the conclusions are not driven by the functional form of the baseline hazard. In practice, this means that while the Cox model leaves the baseline hazard completely unspecified, the Weibull model forces it to follow a particular shape. If both approaches deliver similar results, we can be confident that the main findings are robust and do not depend on how the baseline risk of exit is modelled. On the other hand, if the results diverge, it would suggest that the conclusions are influenced by the choice of functional form, and should therefore be interpreted with greater caution.

Finally, to exploit the discrete annual structure of the data, we estimate *discrete-time hazard models* using a complementary log-log (cloglog) specification. In this approach, the spell is split into firm–year observations, and the exit probability in each year is modelled as

$$Pr(Y_{it} = 1|X_{it}) = 1 - \exp\{-\exp(\alpha_t + \beta' X_{it})\}, \quad (6)$$

where $Y_{it} = 1$ if firm i exits in year t .

The cloglog link is consistent with a continuous-time hazard process while allowing estimation with annual data. This makes it well-suited to the structure of the dataset and offers a flexible way to capture the baseline hazard through duration dummies or splines. It also facilitates the inclusion of time-varying covariates, such as revenues or R&D, although it may encounter problems of perfect prediction when some combinations of duration and covariates contain no exits. In these cases, durations can be grouped or rare interactions removed to retain estimability.

The combination of *Kaplan–Meier*, *Cox*, *Weibull*, and *discrete-time models* ensures that the analysis of firm survival is robust to different distributional assumptions and time representations. Results are reported in terms of hazard ratios, with values above unity indicating higher exit risk and values below unity indicating longer survival.

4.4 Results: Count Data Models

The cross-sectional analysis investigates the firm-level determinants of both the number of Wi-Fi-related patents and their quality, proxied by forward citations. The cross-sectional dataset consists of 194 consolidated firms, each observed over its entire patenting history. Given the discrete and non-negative nature of the dependent variables, number of patents and number of forward citations, Poisson and Negative Binomial (NB) models are employed. To account for the heterogeneous observation windows across firms, the number of years active (exit year – entry year + 1) is included as an exposure term, effectively normalizing patent counts by duration. Results are reported in incidence rate ratios (IRRs), which allow more intuitive interpretation as multiplicative effects on expected patenting rates.

4.4.1 Diagnostics: over-dispersion and robust inference

Patent distributions are highly skewed, with a small number of large firms generating most of the patents and a long tail of smaller assignees. For example, the mean number of patents per firm is approximately 310, while the variance exceeds 2.5 million. This discrepancy strongly indicates overdispersion, that is, the variance of the dependent variable is far larger than its mean.

The Poisson model, which assumes equidispersion, $Var(y_i|X_i) = \mu_i$, provides a poor fit: Pearson goodness-of-fit tests decisively reject the null hypothesis of equidispersion ($p < 0.001$).

By contrast, the Negative Binomial introduces an over-dispersion parameter α , such that

$$Var(y_i|X_i) = \mu_i + \alpha\mu_i^2,$$

and estimates confirm significant over-dispersion in all specifications (α between 2.3 and 3.8). These results justify the use of the NB as the preferred specification for inference, while Poisson estimates are retained as a useful benchmark.

Additionally, all models are estimated with robust (Huber–White) standard errors, which correct inference when heteroskedasticity is present. This is important in cross-

sectional innovation data, where residual variance is likely to differ across firms (for example, larger or older firms may display more volatile outcomes). Robust errors ensure that test statistics and confidence intervals are not biased by distributional assumptions.

4.4.2 Determinants of Patent Number

The first set of regressions estimates the determinants of the number of Wi-Fi patents.

Table 4.1 presents the results of *Poisson* regressions for the number of Wi-Fi-related patents. Because firms enter the patent system in different years and therefore have unequal durations of observation, the regressions include the natural logarithm of the number of years active (*ln_exposure*) as an offset. This adjustment ensures that the dependent variable is interpreted as a patenting rate per year rather than as the absolute number of patents. Without the offset, older firms would mechanically appear more innovative simply because they have been active for longer, rather than because of genuine differences in innovative capacity. The inclusion of exposure, therefore, provides a fair comparison across firms with heterogeneous histories.

Coefficients are reported as Incidence Rate Ratios (IRRs). An IRR greater than one indicates that an increase in the explanatory variable is associated with a higher annual patenting rate, while an IRR below one indicates a decrease. For example, an IRR of 1.33 means that a one-unit increase in the regressor raises the expected patenting rate by 33%.

Robust (Huber–White) standard errors were used in estimation to correct for heteroskedasticity, but are omitted from the table for readability.³

The presence of sector fixed effects (*Sector FE*) is indicated in the table. It allows the models to account for systematic differences in patenting intensity across industries, with Telecommunications as the baseline category.

The variables *Entry year* and *Foundation year* represent firm history controls, capturing the timing of entry into Wi-Fi patenting and the firm's age, respectively.

³ Robust Standard Error results are reported in Table A.1 in the Appendix section

Finally, *Pseudo-R*² is reported as an indicator of model fit: although not directly comparable to *R*² in linear regression, higher values signal that the model explains a greater share of the variation relative to the null specification.

*Table 4.1 – Poisson Regressions for Patent Counts*⁴
(Dependent variable: annual rate of Wi-Fi patents; IRRs reported)

Variables	Poisson (1)	Poisson (2) + Sector FE	Poisson (3) + History
Avg. IPC number	0.86**	0.86*	0.87
Avg. inventor count	1.94***	2.20***	2.28***
Entry year	—	—	1.00
Foundation year	—	—	1.00
Sector FE	No	Yes	Yes
Consumer Electronics & Digital Entertainment		1.12	1.04
Semiconductors & Electronic Components		0.26	0.27
IT, Software, and Cybersecurity		0.59	0.60
Automotive & Industrial Electronics		0.19	0.18
Pseudo-R ²	0.149	0.3384	0.3408

The coefficient on *avg_IPC_number* is consistently below unity, indicating a negative association between technological breadth and patenting intensity. In Column (1), the IRR of 0.86 ($p < 0.05$) suggests that each additional IPC class per patent is associated with a 14% reduction in the annual rate of patenting. The effect persists in Column (2), with the IRR remaining 0.86 ($p < 0.10$) after controlling for sector fixed effects. In Column (3), after including firm history variables, the effect weakens (IRR = 0.87) and loses significance. These results imply that, while technological specialization is associated with higher patenting intensity, the effect is not robust across specifications.

Inventor collaboration emerges as the dominant determinant of patenting intensity. The baseline model yields an IRR of 1.94 ($p < 0.01$), meaning that one additional inventor per patent nearly doubles the expected number of patents filed annually. The effect

⁴ Significance levels are reported as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

strengthens when sector fixed effects are introduced (IRR = 2.20, $p < 0.01$) and remains very strong after including firm history (IRR = 2.28, $p < 0.01$). These results provide compelling evidence that inventor team size is a key driver of innovative capacity in the Wi-Fi domain.

In Column (3), *entry year* (the year of first Wi-Fi patent) and *foundation year* (the firm's founding year) are added to the regression. Both variables are statistically insignificant (IRRs of 1.00). This indicates that, conditional on inventor collaboration, technological scope, and sector, neither the timing of entry nor firm age significantly influences patenting intensity.

Columns (2) and (3) include sector fixed effects, with Telecommunications as the omitted baseline category. The estimated coefficients reveal substantial heterogeneity across industries. Firms in Semiconductors and Electronic Components patent at only about one-quarter the intensity of Telecommunications firms (IRR = 0.26 in Column (2), 0.27 in Column (3)). Similarly, Automotive and Industrial Electronics firms display patenting rates of less than one-fifth compared to Telecommunications (IRR = 0.19 and 0.18, respectively). IT, Software, and Cybersecurity firms also patent significantly less, with IRRs of 0.59–0.60. By contrast, firms in Consumer Electronics and Digital Entertainment show no statistically significant difference from Telecommunications (IRRs close to 1.12 and 1.04). These results confirm that Wi-Fi patenting was highly concentrated in the Telecommunications and Consumer Electronics sectors, while other industries contributed far less.

The Pseudo- R^2 values rise substantially with the inclusion of additional controls: from 0.149 in the baseline model to 0.338 with sector fixed effects and 0.341 with firm history variables. This progression indicates a considerable improvement in explanatory power when accounting for sectoral heterogeneity, while firm history adds little further explanatory value.

Taken together, the results of Table 4.1 highlight three key findings. First, inventor team size is the most robust determinant of Wi-Fi patenting intensity: firms with larger inventor teams produce significantly more patents per year. Second, technological breadth shows a negative association with patenting, suggesting that specialization is more

conducive to innovative output, although the effect is not robust once firm history is added. Third, sectoral affiliation is crucial: Telecommunications and Consumer Electronics dominate the Wi-Fi patent landscape, while Semiconductors, IT/Software, and Automotive firms patent at substantially lower rates. By contrast, firm age and entry timing have no significant impact.

Overall, the Poisson results with exposure confirm that collaboration among inventors and industry positioning, rather than age or breadth, explain which firms were most active in shaping the Wi-Fi technological trajectory.

The Poisson regressions provided a useful starting point, but they rely on the restrictive assumption of equidispersion, which occurs when the variance of the dependent variable equals its mean. In the context of Wi-Fi patents, this assumption is not realistic. As shown in the descriptive statistics (Chapter 3), the distribution of patents is extremely skewed, with many firms filing only a few patents while a few firms, such as major telecommunications equipment manufacturers, accumulate very large portfolios. This generates a variance larger than the mean, a condition referred to as over-dispersion.

When over-dispersion is present, the Poisson model tends to understate standard errors and exaggerate the statistical significance of covariates. To address this issue, the Negative Binomial (NB) model introduces an additional parameter, denoted α , which explicitly captures the extent of over-dispersion. Formally, while the variance in the Poisson is given by $\text{Var}(y|X) = \mu$, in the NB model it is $\text{Var}(y|X) = \mu + \alpha\mu^2$. When $\alpha = 0$, the NB collapses to the Poisson, but when α is significantly greater than zero, the NB provides a strictly better fit to the data.

Table 4.2 – Negative Binomial Regressions for Patent Counts⁵

(Dependent variable: annual rate of Wi-Fi patents; IRRs reported)

Variables	NB (1)	NB (2) + Sector FE	NB (3) + History
Avg. IPC number	1	1.05	1.09**
Avg. inventor count	2.75***	1.54**	1.26**
Entry year	—	—	0.93
Foundation year	—	—	1.00
Sector FE	No	Yes	Yes
Consumer Electronics & Digital Entertainment		0.91	0.54
Semiconductors & Electronic Components		0.32	0.3
IT, Software, and Cybersecurity		0.1	0.17
Automotive & Industrial Electronics		0.2	0.18
Pseudo-R ²	0.018	0.056	0.075
α (overdispersion)	2.28***	1.75***	1.52***

Table 4.2 presents the results of Negative Binomial (NB) regressions for the annual rate of Wi-Fi patents. As discussed earlier, patent counts display substantial overdispersion: many firms patent very little, while a few firms account for a very large share of total activity. This generates a variance far greater than the mean, which violates the equi-dispersion assumption of the Poisson model. The NB model explicitly addresses this issue by introducing the dispersion parameter α , which is estimated to be positive and highly significant across all specifications (2.28, 1.75, and 1.52, respectively; $p < 0.01$). These results formally reject the null hypothesis of equi-dispersion ($\alpha = 0$) and confirm that the NB is statistically superior to the Poisson.

The coefficients on *avg_IPC_number* indicate that technological breadth is not a consistent predictor of patenting intensity. In the baseline NB regression (Column 1), the IRR is exactly one, suggesting no relationship between IPC scope and patenting. With sector fixed effects (Column 2), the effect remains statistically insignificant (IRR = 1.05). Only in the full specification including firm history (Column 3) does the coefficient

⁵ Significance levels are reported as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

become marginally significant (IRR = 1.09, $p < 0.05$), implying that each additional IPC class per patent increases patenting intensity by around 9%. However, given the absence of robustness across models, this effect should be interpreted cautiously

Inventor collaboration remains the most powerful and robust determinant of Wi-Fi patenting activity. In the baseline model (Column 1), the IRR is 2.75 ($p < 0.01$), meaning that one additional inventor per patent is associated with a 175% increase in the annual rate of patenting. Although the effect attenuates once sector fixed effects are added (IRR = 1.54, $p < 0.05$) and further when firm history is included (IRR = 1.26, $p < 0.05$), the variable remains significant. This confirms that inventor team size is a key driver of innovative capacity, even though the magnitude of the effect is moderated when taking into consideration structural differences across sectors and firm history.

The inclusion of firm history variables in Column (3) shows no significant effects. The IRR for the entry year is 0.93 and for the foundation year 1.00, both statistically indistinguishable from unity. This suggests that neither the age of the firm nor the timing of entry into Wi-Fi patenting significantly shapes patenting intensity once collaboration and sectoral affiliation are taken into account.

The coefficients on industry dummies highlight large and systematic differences across sectors. Compared to Telecommunications (the reference category), all other industries patent significantly less intensively in the Wi-Fi domain. The greatest gap is observed for IT, Software, and Cybersecurity, where the IRR is as low as 0.10 in Column (2) and 0.17 in Column (3), meaning these firms patent only about one-tenth to one-fifth as much as Telecommunications firms. Similarly, Automotive and Industrial Electronics firms patent at less than one-fifth the intensity of Telecommunications (IRRs of 0.20 and 0.18). Firms in Semiconductors and Electronic Components also lag behind (IRRs of 0.32 and 0.30). The only sector with patenting rates approaching parity is Consumer Electronics and Digital Entertainment, though even here the effect is below unity once firm history is included (IRR = 0.54). These results underline the central role of Telecommunications and Consumer Electronics in driving Wi-Fi innovation.

The Pseudo- R^2 values are modest in absolute terms, as is common in count data models, but increase substantially with the inclusion of sector and firm history controls

(from 0.018 to 0.075). Notably, the α parameter is large and highly significant in all models, confirming that over-dispersion is a structural feature of Wi-Fi patent data. This provides strong statistical evidence that the Poisson specification is inadequate and that the NB is the preferred estimator.

Overall, the evidence indicates that inventor collaboration and sectoral affiliation, particularly within Telecommunications and Consumer Electronics, are the fundamental drivers of Wi-Fi patenting intensity, while firm history and technological diversification play a marginal role.

4.4.3 Determinants of Patent Quality

Forward citations represent a widely used proxy for assessing the technological and economic value of patents, as they capture the extent to which subsequent innovations build upon a firm's inventions (Trajtenberg 1990). In this section, the number of forward citations received by Wi-Fi-related patents is employed as the dependent variable. As with patent counts, the regressions are estimated with an exposure term, normalizing by the years of observation. This ensures that results are expressed as citation rates per year, making firms comparable despite heterogeneous observation periods. As before, three specifications are considered: (1) patent-level characteristics, (2) addition of sector fixed effects, and (3) inclusion of firm history controls.

Table 4.3 – Poisson Regressions for Forward Citations⁶
(Dependent variable: annual rate of forward citations; IRRs reported)

Variables	Poisson (1)	Poisson (2) + Sector FE	Poisson (3) + History
Avg. IPC number	0.8**	0.81**	0.88
Avg. inventor count	1.86***	2.1***	2.49***
Entry year	—	—	0.98***
Foundation year	—	—	1.0
Sector FE	No	Yes	Yes
Consumer Electronics & Digital Entertainment		0.64	0.46
Semiconductors & Electronic Components		0.12	0.15
IT, Software, and Cybersecurity		0.1	0.12
Automotive & Industrial Electronics		0.23	0.19
Pseudo-R ²	0.1485	0.3419	0.4377

The variable *avg_IPC_number* consistently shows coefficients below unity in Columns (1) and (2), with IRRs of 0.80 and 0.81 (both $p < 0.05$). This indicates that firms whose patents cover more technological classes receive fewer forward citations per year. A plausible interpretation is that specialization leads to patents with clearer technological relevance and therefore higher citation rates, whereas diversified patents may be less central to subsequent innovation. In Column (3), however, the coefficient becomes statistically insignificant (IRR = 0.88), suggesting that this effect is not robust once firm history is considered.

Inventor collaboration remains a highly significant determinant of patent quality. The IRR rises from 1.86 in Column (1) to 2.10 in Column (2), and further to 2.49 in Column (3), all significant at the 1% level. This implies that each additional inventor per patent increases the expected number of forward citations per year by 86–149%. These results highlight that inventor teams not only enhance the quantity of patenting, as shown in earlier sections, but also improve the impact of patents in terms of knowledge diffusion.

⁶ Significance levels are reported as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

When firm history is included in Column (3), the variable *entry year* is significant and below unity (IRR = 0.98, $p < 0.01$). This suggests that later entrants into Wi-Fi patenting receive fewer forward citations, reflecting a possible first-mover advantage: early innovators may have had greater opportunities to influence subsequent technological developments. By contrast, the *foundation year* remains insignificant (IRR = 1.00), indicating that the age of the firm per se does not matter once the timing of entry is controlled for.

Sectoral differences are large and persistent. In Column (2), compared to Telecommunications (the reference category), all other sectors show much lower citation rates: Consumer Electronics firms exhibit IRRs of 0.64, Semiconductors 0.12, IT/Software 0.10, and Automotive 0.23. These results indicate that Telecommunications firms produce patents that are far more frequently cited than those in other industries. When firm history is added in Column (3), the pattern remains unchanged, with IRRs of 0.46, 0.15, 0.12, and 0.19, respectively. This confirms that the Telecommunications sector was the main focus of high-impact Wi-Fi innovation.

The Poisson regressions on forward citations point to three main results. First, inventor team size emerges as a strong and consistent driver of patent quality: patents developed by larger inventor groups systematically receive more citations. Second, the timing of entry also plays a role, with early entrants into Wi-Fi patenting enjoying a clear advantage in terms of subsequent citations, in line with the idea of first-mover benefits. Third, sectoral affiliation proves to be crucial: Telecommunications firms not only produced a larger volume of patents but also generated innovations of greater technological impact, while other sectors contributed significantly less. By contrast, technological breadth appears less relevant, with a weak negative association that disappears once firm history is taken into account.

Table 4.4 – Negative Binomial Regressions for Forward Citations
(Dependent variable: annual rate of forward citations; IRRs reported)

Variables	NB (1)	NB (2) + Sector FE	NB (3) + History
Avg. IPC number	1.0	1.02	1.07
Avg. inventor count	1.85**	1.30	1.06
Entry year	—	—	0.84***
Foundation year	—	—	1.01***
Sector FE	No	Yes	Yes
Consumer Electronics & Digital Entertainment		0.76	0.40
Semiconductors & Electronic Components		0.14	0.14
IT, Software, and Cybersecurity		0.21	0.53
Automotive & Industrial Electronics		0.24	0.54
Pseudo-R ²	0.0037	0.0133	0.0538
α (overdispersion)	4.07***	3.70***	2.43***

Table 4.4 presents the results of Negative Binomial (NB) regressions for forward citations. As with patent counts, forward citation data display strong over-dispersion: many patents receive no or very few citations, while a limited number accumulate disproportionately high counts. The Poisson model is therefore likely to underestimate standard errors. The NB specification addresses this issue through the dispersion parameter α , which is large and highly significant in all specifications (4.07, 3.70, 2.43; $p < 0.01$), confirming that over-dispersion is a structural feature of citation data. This makes the NB the preferred estimator for modelling patent quality.

Across all specifications, the coefficients for *avg_IPC_number* remain close to unity and statistically insignificant (IRRs between 1.00 and 1.07). This indicates that the technological breadth of patents does not exert a systematic influence on their likelihood of being cited, once over-dispersion is accounted for. The weak negative effect detected in some Poisson models, therefore, appears to be spurious.

Inventor collaboration is still positively associated with patent impact, but the magnitude of the effect is smaller and less robust than in the Poisson models. In the

baseline NB (Column 1), the IRR is 1.85 ($p < 0.05$), implying that patents developed by larger inventor teams receive significantly more forward citations per year. However, the effect weakens substantially once sector fixed effects are included (IRR = 1.30, not significant) and almost disappears when firm history is added (IRR = 1.06). This suggests that the apparent strong effect of inventor collaboration on patent impact is partly explained by sectoral and temporal heterogeneity.

Firm history variables provide additional insights in Column (3). The coefficient on *entry year* is 0.84 ($p < 0.01$), indicating that firms entering later into Wi-Fi patenting receive fewer citations per year. This result reflects a clear first-mover advantage, where early entrants were able to shape the technological trajectory and accumulate more impactful patents. By contrast, the *foundation year* is estimated at 1.01 ($p < 0.01$), though the effect size is very close to unity. The statistical significance here likely reflects the large sample size rather than a clear economic effect, showing that firm age has a minor influence on patent quality.

The inclusion of sector dummies reveals strong differences across industries. Compared to Telecommunications (the baseline), firms in Consumer Electronics receive fewer citations (IRR = 0.76 in Column 2, 0.40 in Column 3). The gap is even larger for Semiconductors, with IRRs of 0.14 in both specifications, and for IT/Software, where IRRs range between 0.21 and 0.53. Automotive and Industrial Electronics also show citation rates well below Telecommunications, with IRRs of 0.24 and 0.54. These results confirm that high-impact Wi-Fi patents were concentrated in Telecommunications, while other sectors contributed innovations of more limited technological visibility.

The Negative Binomial regressions show that patent quality in Wi-Fi is shaped especially by entry timing and sectoral affiliation. Early entrants produced more highly cited patents, and Telecommunications firms stand out for their technological impact. Inventor collaboration remains positive but weaker than in the Poisson results, while technological breadth and firm age do not play a significant role.

These findings describe what drives the propensity to innovate and the quality of innovation, but they do not address the important question of whether patenting activity translates into superior firm performance.

To address this second dimension, the next section focuses on panel regressions combining patenting data with firm-level financial indicators. By linking patent activity to revenues and other economic outcomes, this analysis explores whether firms that patent more intensively in Wi-Fi also achieve stronger performance in the marketplace.

4.5 Results: Panel Regressions

The panel analysis builds on the merged dataset of 68 firms, obtained by integrating Wi-Fi patent data with annual financial information from *Compustat*. This firm–year panel allows an investigation of whether patenting activity is associated with superior economic performance.

The dependent variable is the natural logarithm of firm revenues. The log transformation reduces the skewness of the revenue distribution and allows regression coefficients to be interpreted as elasticities: they measure the percentage change in revenues associated with a one-percent change in the explanatory variables.

The main explanatory variable is the logarithm of patent counts, expressed as $\ln(1+patents)$. This functional form enables the inclusion of firms with zero patents (the +1 prevents the logarithm from being undefined) and attenuates the influence of extreme values, which are common in innovation data.

Two additional control variables are considered:

- Firm size, proxied by the log of the number of employees ($\ln(employees)$), which captures the scale of operations. Larger firms are expected to generate higher revenues due to economies of scale and broader market reach.
- R&D expenditures, also in logarithmic form ($\ln(R\&D\ expenditures)$), which reflect the intensity of investment in innovation and are typically linked to higher productivity and growth.

All specifications include year fixed effects, which absorb shocks that affect all firms in a given year (such as macroeconomic cycles or crises), ensuring that the coefficients capture within-firm dynamics rather than common external influences.

Finally, the regressions are estimated with robust standard errors clustered at the firm level, correcting for heteroskedasticity and potential autocorrelation in the panel structure. This makes the inference more reliable and robust to firm-specific shocks over time.

Table 4.5 - Panel Regressions of Revenues on Patenting Activity⁷

Variables	Model (1) Baseline	Model (2) + Size	Model (3) + Size & R&D
ln(1+Patents)	0.592***	0.042	0.023
ln(Employees)	—	1.002***	0.778***
ln(R&D expenditures)	—	—	0.271***
R ²	2.1504	0.9343	0.9390

In the baseline model, revenues depend only on patenting activity and year fixed effects. The coefficient on $\ln(1+patents)$ is 0.592 and highly significant ($p < 0.01$). This implies that, on average, a 1% increase in patent counts is associated with a 0.59% increase in revenues. This strong and significant relationship suggests a positive correlation between innovative output and firm performance. However, since no controls are included, the result should be interpreted with caution. The R² of 2.15 indicates some explanatory power but also reflects potential omitted variable bias.

When firm size is added as a control, the coefficient on $\ln(1+patents)$ falls sharply to 0.042 and loses statistical significance. At the same time, the effect of $\ln(employees)$ is large and highly significant (1.002, $p < 0.01$). This suggests that revenues scale almost proportionally with workforce size, reflecting economies of scale and broader market capacity. The explanatory power of the model increases, with R² rising to 0.934. The sharp decline in the patent coefficient indicates that the baseline correlation was mainly driven by firm size: larger firms both patent more and generate higher revenues.

In the full specification, which includes both firm size and R&D spending, the coefficient on $\ln(1+patents)$ decreases further to 0.023 and remains insignificant. By

⁷ Significance levels are reported as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered at the firm level.

contrast, $\ln(\text{employees})$ remains strongly significant (0.778, $p < 0.01$), and $\ln(\text{R\&D expenditures})$ enters with a positive and highly significant effect (0.271, $p < 0.01$). This highlights that revenues are mainly driven by resources and capabilities, firm size and R&D investment, rather than by patent counts. The model's explanatory power improves slightly, with R^2 reaching 0.939.

4.5.1 Robustness Checks

In the innovation literature, R&D intensity, measured as the ratio of R&D expenditures to firm revenues, is often used as an indicator of innovative effort relative to firm size. For this study, the variable was calculated for the sample firms and carefully examined. However, its distribution turned out to be highly skewed: while the median stood at about 7%, some firms reported implausibly high values, in certain cases above 100% and even exceeding 4000%. These extreme outcomes typically occurred in years when revenues were very low or negative, artificially increasing the ratio and undermining its interpretability.

For this reason, the variable was not included in the panel regressions. Instead, the log of R&D expenditures was used as a control, as it provides more stable results and avoids distortions from extreme cases. Additional checks with winsorized and capped versions of R&D intensity confirmed that the distribution remained problematic and that specifications based on R&D expenditures in levels produced more consistent and reliable results.

The panel regressions have shown that firm revenues are primarily driven by size and R&D expenditures, while the direct effect of Wi-Fi patenting activity appears limited once these factors are taken into account. This perspective shows the importance of resources and capabilities in shaping economic performance, but it does not address another crucial dimension of firm dynamics: the ability to survive over time after entering Wi-Fi-related innovation.

To complement the analysis, the next section turns to survival models, where the event of interest is firm exit from the dataset. This approach allows an investigation of whether firm characteristics observed at entry (revenues, R&D effort, and size) affect the probability of remaining active in Wi-Fi patenting. By combining non-parametric, semi-

parametric, and parametric methods, the survival analysis provides an additional dimension to the empirical analysis, focusing on the long-term resilience of innovative firms.

4.6 Results: Survival Analysis

An important dimension of innovative dynamics is whether firms manage to survive after entering Wi-Fi-related patenting. Survival analysis provides the necessary tools to investigate this question, since it focuses on the duration until an event occurs, in this case, intended as the exit of a firm from the *Compustat* database.

The survival dataset was constructed at the firm level for the 39 companies for which both patent and *Compustat* financial data are available. For each firm, the following variables were defined:

- Entry year: the year of the first Wi-Fi-related patent.
- Exit year: the last year in which the firm appears in *Compustat*. If the firm remains active until the end of the observation window, the observation is treated as right-censored.
- Event indicator: equal to 1 if the firm exits before the end of the panel, and 0 if it is censored.
- Spell: the number of years between entry and exit.
- Covariates at entry: revenues, R&D expenditures, employees, and R&D intensity, all measured in the entry year (or in entry+1 when entry-year data were not available).

The analysis is carried out in stages, reflecting the different levels of structure that can be imposed on the baseline hazard:

- 1) Non-parametric estimation using Kaplan-Meier survival functions, which provide descriptive evidence of survival probabilities across cohorts without imposing distributional assumptions.
- 2) Semi-parametric. Estimation with the Cox proportional hazards model, where the hazard rate depends on firm covariates while leaving the baseline hazard unspecified. This model yields hazard ratios (HRs), which measure how firm characteristics affect the probability of exit at any point in time.
- 3) Parametric estimation with the Weibull proportional hazards model, which

assumes a monotonic shape of the baseline hazard. This approach allows verification that results are not driven by the functional form of the hazard function.

- 4) Discrete-time estimation with a complementary log-log (cloglog) specification, where spells are converted into firm-year observations. This is particularly suited to datasets recorded annually and allows the inclusion of time-varying covariates.

4.6.1 Non-parametric analysis

Figure 4.1 displays the Kaplan–Meier survival curve for the full sample of 39 firms. The curve shows a gradual decline in survival probability during the first decade, followed by a sharper drop after 20 years. Around 25–30 years after entry, the survival probability falls below 50%, and only a few firms remain active after 40 years. This pattern highlights that Wi-Fi innovators face a limited life cycle, with increasing competitive pressures over time.

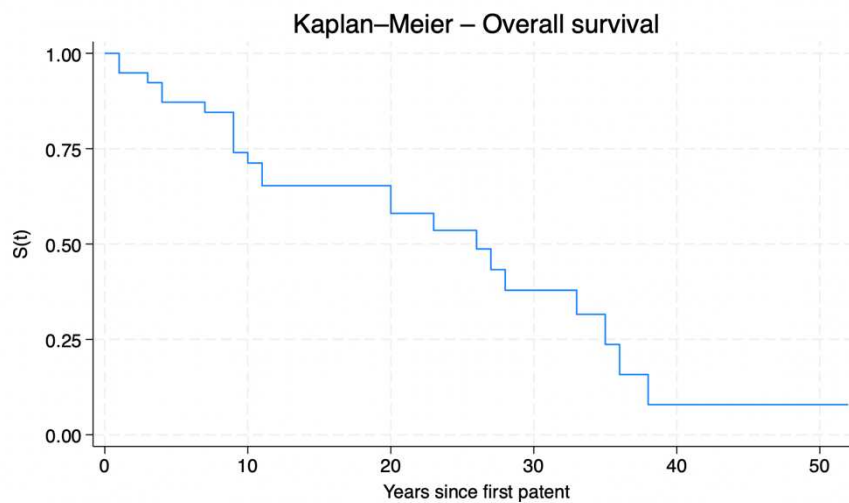


Figure 4.1 – Kaplan-Meier Survival Curve for Wi-Fi Innovators

Figure 4.2 plots survival functions by entry cohort. The differences are crucial: early entrants (pre-1995) show significantly higher survival probabilities, with several firms remaining active for more than three decades. By contrast, firms entering between 1995 and the mid-2000s show survival probabilities dropping below 50% within 20 years. The most recent entrants (post-2005) also face a higher hazard of exit, though their shorter observation window prevents a direct comparison with earlier cohorts. Overall, the evidence is consistent with the presence of a first-mover advantage, as pioneering firms

enjoyed higher survival rates, likely due to lower initial competition and greater opportunities to consolidate their technological position.

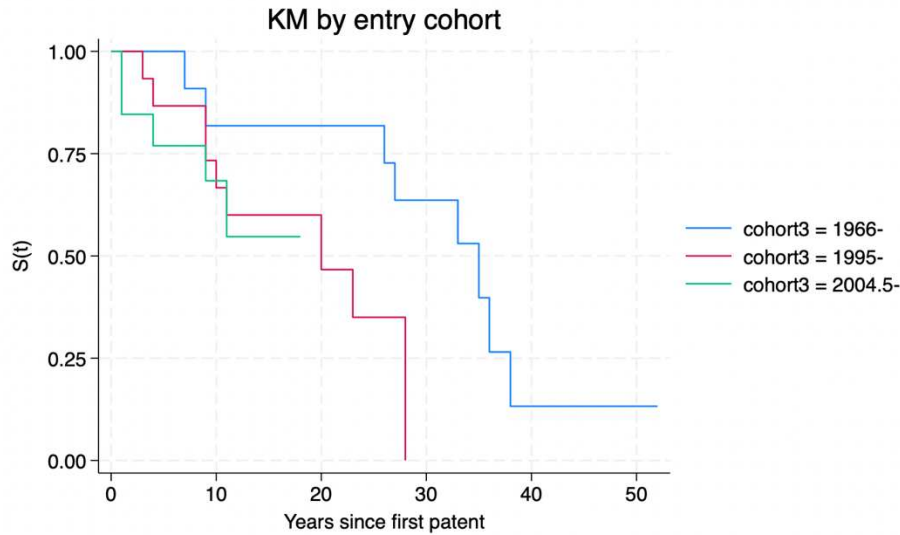


Figure 4.2 - Kaplan-Meier Survival Curve by Entry Cohort

Additional Kaplan–Meier plots split the sample by terciles of revenues, R&D expenditure, and employees⁸. In all cases, firms with higher initial resources exhibit higher survival probabilities. For example, high-revenue firms maintain substantially greater survival rates compared to low-revenue firms, especially after 15 years. Firms with greater R&D expenditure and larger employee bases display similar advantages, reinforcing the idea that economic and innovative resources support longer survival in Wi-Fi patenting.

Overall, the descriptive evidence indicates that firms with stronger resources at the time of entry are more likely to survive in the long run. This underlines the role of both economic and innovative capacity as key factors for sustaining activity in the Wi-Fi domain.

⁸ See Figure A.1 in the Appendix section

4.6.2 Cox Proportional Hazards

Table 4.6 reports the results of the Cox proportional hazards regression, estimated with robust standard errors clustered at the firm level. The model provides a multivariate assessment of how firm-level characteristics measured at entry influence exit probability.

The estimates highlight two clear patterns. First, firm size has a protective effect on survival. The coefficient for employment ($\ln_employees$) is significantly below unity (HR ≈ 0.62 , $p < 0.05$), indicating that larger firms face a reduced risk of exit. This result is consistent with the descriptive Kaplan–Meier evidence, confirming that firms with stronger organizational capacity are more resilient over time.

Second, revenues display a counterintuitive effect. The hazard ratio for revenues ($\ln_revenues$) exceeds unity (HR ≈ 1.55 , $p < 0.05$), suggesting that firms with higher revenues at entry face a higher risk of exit. Several explanations may account for this finding. Revenues and employment are strongly correlated, and once size is controlled for, the revenue coefficient may capture volatility or extraordinary dynamics in the years surrounding entry. Another possible interpretation is that some exits in the dataset correspond to mergers and acquisitions. For this reason, the revenue effect should be interpreted with caution.

R&D expenditures, in contrast, do not exhibit a statistically significant effect (HR ≈ 1.0 , $p > 0.10$). This may reflect limited variation in the data, as many firms report zero or very low R&D spending, which reduces the power of the variable.

Finally, cohort dummies show systematic differences in survival across entry waves. Compared to early entrants, firms that entered the Wi-Fi domain after 1995 show higher exit risks. In particular, late entrants (post-2005) exhibit hazard ratios more than four times higher than early entrants (HR ≈ 4.40 , $p \approx 0.056$). Although only marginally significant, this pattern aligns with the Kaplan–Meier results and supports the idea of a first-mover advantage, with pioneering firms enjoying superior long-term survival prospects.

Table 4.6 – Cox Proportional Hazards Regression Results (Dependent variable: firm exit)⁹

Variables	Hazard Ratio	Std. Err.	p-value	95% Conf. Interval
ln(revenues)	1.549**	0.317	0.033	1.037 – 2.314
ln(employees)	0.616**	0.135	0.027	0.401 – 0.947
R&D expenditure	1.000	0.000	0.104	1.000 – 1.000
Cohort 1995–2004.5	3.035	2.153	0.118	0.756 – 12.190
Cohort post-2005	4.397*	3.405	0.056	0.964 – 20.058

Log pseudolikelihood -47.901611

Number of obs	35
Wald chi2(5)	18.16
Prob > chi2	0.0027

4.6.3 Robustness Checks

To assess the robustness of the survival results, two alternative specifications were estimated: a parametric Weibull proportional hazards model and a discrete-time hazard model with complementary log-log (cloglog) link. These approaches complement the Cox model by imposing different assumptions on the baseline hazard and the time structure of the data.

⁹ Significance levels are reported as: *** p<0.01, ** p<0.05, * p<0.10. Robust standard errors clustered at the firm level.

Weibull proportional hazards model

Table 4.7 reports the Weibull regression results. The main coefficients are consistent with those obtained in the Cox model. Revenues remain positively associated with the hazard of exit ($HR \approx 1.52$, $p < 0.05$), while employment retains a protective effect ($HR \approx 0.65$, $p \approx 0.05$). R&D expenditure does not exert a significant influence.

A key advantage of the Weibull model is the estimation of the shape parameter p . In this case, $p = 1.51$ ($p \approx 0.07$), which is greater than one. This indicates that the hazard of exit increases over time, consistent with the idea that competitive pressures and technological obsolescence intensify as the Wi-Fi standard matures. The similarity between Cox and Weibull results strengthens confidence that the findings are not driven by the functional form of the baseline hazard.

Table 4.7 - Weibull Proportional Hazards Regression Results (Dependent variable: firm exit)¹⁰

Variables	Hazard Ratio	Std. Err.	p-value	95% Conf. Interval
ln(revenues)	1.523**	0.303	0.034	1.032 – 2.250
ln(employees)	0.649*	0.144	0.051	0.419 – 1.002
R&D expenditure	1.000	0.000	0.140	1.000 – 1.000
Cohort 1995–2004.5	1.652	0.804	0.302	0.637 – 4.286
Cohort post-2005	2.628*	1.492	0.089	0.863 – 7.996
Shape parameter (p)	1.507*	0.345	0.073	0.962 – 2.359

Log pseudolikelihood -36.531181

Number of obs	35
Wald chi2(4)	.
Prob > chi2	.

¹⁰ Significance levels are reported as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered at the firm level.

Discrete-time cloglog model

As an additional robustness check, the survival analysis was replicated in discrete time by splitting each firm's spell into annual firm-year observations and estimating a complementary log-log (cloglog) model. This approach is particularly suitable for datasets recorded in yearly intervals, as it allows the baseline hazard to be represented more flexibly through the use of time dummies. The cloglog link remains consistent with a continuous-time hazard process, making the results directly comparable with those of the Cox and Weibull models.

The main findings are in line with previous specifications. Higher revenues are again associated with a greater risk of exit ($HR \approx 1.67$, $p < 0.05$), while larger employment reduces it ($HR \approx 0.58$, $p < 0.05$). As before, R&D expenditure does not appear to play a significant role. These results confirm the central importance of firm size in sustaining survival and the surprisingly positive association between revenues and exit, which may reflect acquisition dynamics or revenue volatility rather than genuine weakness.

During estimation, one practical difficulty was the problem of *perfect prediction*. When yearly dummies were included, some years contained only survivors while others only exits. In such cases, the time dummy perfectly predicts the outcome, making it impossible to estimate a finite coefficient. To overcome this issue, the baseline was aggregated into five-year intervals, ensuring that each category contained both events and non-events.

The specification with five-year intervals produces stable results and indicates a clear upward trend in the baseline hazard. The risk of exit increases with time spent in the Wi-Fi patenting domain, with a marked rise after approximately twenty years from entry. This evidence reinforces the conclusions from the Weibull model: survival becomes progressively harder as competition intensifies and technologies age, leaving only a few resilient firms active in the long run.

Table 4.8 - Discrete-time Cloglog Regression Results (Dependent variable: firm exit)¹¹

Variables	Hazard Ratio	Std. Err.	p-value	95% Conf. Interval
ln(revenues)	1.670**	0.420	0.041	1.021 – 2.732
ln(employees)	0.583**	0.168	0.037	0.354 – 0.958
R&D expenditure	1.000	0.000	0.227	1.000 – 1.000
Cohort 1995–2004.5	1.745	0.940	0.295	0.615 – 4.949
Cohort post-2005	2.834*	1.623	0.092	0.850 – 9.446
Time (five-year dummies)	Yes	—	—	—

Log pseudolikelihood	-49.595857
Number of obs	169
Wald chi2(13)	.
Prob > chi2	.

4.6.4 Discussion of Survival Analysis

The survival analysis provides a comprehensive picture of the dynamics of firm exit in the Wi-Fi domain. Across non-parametric (Kaplan–Meier), semi-parametric (Cox), parametric (Weibull), and discrete-time (cloglog) approaches, a consistent set of findings emerges.

First, firm size is the most robust determinant of survival. Both the descriptive Kaplan–Meier curves and the multivariate regressions indicate that firms with more employees face significantly lower exit risks. This result underscores the role of organizational resources and capacity in sustaining innovative activity over time.

¹¹ Standard errors clustered at the firm level. Time measured in five-year intervals to avoid perfect prediction. Significance levels are reported as: **p < 0.05, *p < 0.10.

Second, revenues are positively associated with exit risk, a finding that may appear counterintuitive. One possible explanation is that larger and more profitable firms are also more likely to be targets of mergers and acquisitions, which in the dataset are indistinguishable from genuine failures. Otherwise, the effect may reflect revenue volatility: firms experiencing rapid increases in revenues at entry may be more exposed to subsequent decline or restructuring.

Third, R&D expenditures do not exert a consistent effect on survival. This likely reflects the limitations of the dataset, where several firms report no R&D spending in Compustat. As a result, absolute R&D levels provide little explanatory power once revenues and size are controlled for.

Finally, entry timing matters. Both Kaplan–Meier curves and regression results suggest that firms entering the Wi-Fi trajectory later face higher hazards, consistent with the notion of a first-mover advantage. Early entrants enjoyed longer survival prospects, while later cohorts faced competition and less opportunities.

The robustness checks strengthen confidence in these findings. The Weibull model indicates that the baseline hazard increases with time, consistent with cumulative competitive pressures. The cloglog specification confirms the main effects while addressing the discrete-time structure of the data.

4.7 Conclusion

This chapter examined the determinants and consequences of Wi-Fi–related patenting using three econometric approaches: count data models, panel regressions, and survival analysis. Each addressed a specific research question, and together they provide an explanation of how firms engaged with the technological trajectory shaped by Wi-Fi standardization.

The count data models show that patenting output and impact were mainly driven by inventive collaboration and sectoral affiliation. Larger inventor teams generated more patents and more highly cited ones, while telecommunications firms dominated in terms of both volume and quality. Entry timing also mattered: early entrants benefited from a clear

citation advantage, pointing to first-mover benefits. By contrast, technological breadth and firm age were not robust predictors once other factors were included.

The panel regressions explored whether patenting translated into superior economic performance. While a simple specification suggested a positive link between patents and revenues, this effect disappeared once firm size and R&D spending were included. Instead, employment and R&D expenditures emerged as the strongest predictors of revenues, suggesting that patents reflect underlying resources rather than driving performance on their own.

The survival analysis examined how entry characteristics influenced firm longevity. Across Cox, Weibull, and cloglog models, larger firms proved more resilient, while revenues showed a counterintuitive positive association with exit, possibly reflecting acquisitions or revenue volatility. R&D expenditures did not have a systematic effect. Again, entry timing was important: early entrants survived longer, while later cohorts faced higher risks. The Weibull and cloglog models also indicated that exit risks rise over time, consistent with increasing competition and technological obsolescence.

Overall, the evidence suggests that innovation in the Wi-Fi domain was shaped by collaboration and sectoral dynamics, but that long-term performance and survival depended more on resources and timing than on patent counts alone. Larger firms with substantial R&D capacity were more able to convert innovation into revenues and face competitive pressures, while early entrants enjoyed advantages that later firms could not have.

These findings highlight a broader lesson: patents are a visible signal of innovation, but their economic and strategic meaning depends heavily on the resources of the firms that hold them and on the moment they chose to enter the technological race.

CONCLUSIONS

This thesis explored the relationship between technological standardization and innovation through the Wi-Fi case, one of the most emblematic technologies of the contemporary digital economy. By combining literature review, patent data analysis, and econometric evidence, the study showed how the standardization processes may act both as factors that incentivize innovation and as mechanisms that reshape market competition and industrial structure.

From a theoretical perspective, this thesis has shown that patents not only represent instruments that protect innovation, but also strategic assets used by firms to access technology markets, negotiate agreements, and position themselves within standardization processes. In the case of Wi-Fi, the interaction between essential patents and open standardization created a distinctive balance between cooperation and competition, in which the knowledge sharing and technological integration have contributed to the global diffusion of technology.

The empirical analysis on Wi-Fi-related patents confirmed that standardization significantly impacted the innovative dynamic of the firms involved. Evidence shows that patenting activity increased notably after adopting the IEEE 802.11 standard, measured by citations, both in terms of volume and quality of patents. Firms that actively participated in standardization processes or that contributed with Standard Essential Patents (SEPs) showed higher levels of innovation and a greater likelihood of remaining active in the technological market.

Like any empirical study, this research has some limitations that should be acknowledged. The first concerns the quality and the availability of the patenting data. Even though the dataset covers a long period and includes a high number of firms, information on patent holders and their economic characteristics is not always complete or perfectly updated. In some cases, it was necessary to proceed through a manual reclassification, which might have introduced some bias. A second limitation regards the use of patents as a measure of innovation. Patenting data does not capture all the dimensions of the innovative activity: not all inventions are patented, and not all patents

represent real technological advancements. Finally, the small sample size and the specific nature of the Wi-Fi case limit the possibility of completely generalizing the results to other sectors or other standardization processes. Nevertheless, despite such limitations, the analysis provides a coherent picture of the relationship between standardization and innovation and sets the foundation for future research.

Overall, the Wi-Fi case confirms that technological standardization can be a strong engine for collective innovation, provided that it is supported by patent disclosure rules and governance mechanisms that balance openness with incentives for research and development.

From a policy point of view, results suggest the relevance of promoting open and interoperable standards that can encourage technology diffusion without compromising firms' motivation to innovate. At the same time, authorities should supervise the concentration effects and the entry barriers that can arise when essential patents are controlled by a small number of dominant players.

In conclusion, the research provides a foundation for future studies related to other cases of standardization, such as 5G networks or artificial intelligence, where the relationship between innovation, competition, and cooperation keeps reshaping the evolution of the digital economy.

BIBLIOGRAPHY

- Arora, Ashish, Andrea Fosfuri, and Alfonso Gambardella. 2001. *Markets for Technology: The Economics of Innovation and Corporate Strategy*. MIT Press.
- Bekkers, Rudi, and Arianna Martinelli. 2012. *Knowledge Position in High-Tech Markets: Network Analysis of European ICT Standardization*. 41 (3): 487–98.
- Bessen, James, and Eric Maskin. 2009. ‘Sequential Innovation, Patents, and Imitation’. *Wiley-Blackwell* 40 (4): 611–35.
- Blind, Knut, Jakob Edler, Rainer Frietsch, and Ulrich Schmoch. 2010. *Motives to Patent: Empirical Evidence from Germany*. 35 (5): 655–72.
- Bound, John, Clint Cummins, Zvi Griliches, Bronwyn H. Hall, and Adam B Jaffe. 1984. ‘Who Does R&D and Who Patents?’ *University of Chicago Press*.
- Cameron, Adrian Colin, and Pravin K. Trivedi. 2013. *Regression Analysis of Count Data*. 2nd edition. Econometric Society Monographs 30. Cambridge University Press.
- Cohen, Wesley M., Richard R. Nelson, and John P. Walsh. 2000. *Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not)*. NBER Working Paper.
- Cox, David R. 1972. ‘Regression Models and Life-Tables’. *Journal of the Royal Statistical Society: Series B (Methodological)* 34 (2).
- David, Paul A., and Shane Greenstein. 1990. ‘The Economics of Compatibility Standards: An Introduction to Recent Research’. In *Economics of Innovation and New Technology*, vol. 1. Taylor & Francis.
- Farrell, Joseph, and Garth Saloner. 1985. ‘Standardization, Compatibility, and Innovation’. *Wiley-Blackwell* 16 (1): 70–83.
- Farrell, Joseph, and Garth Saloner. 1986. ‘Installed Base and Compatibility: Innovation, Product Preannouncements, and Predation’. *American Economic Association* 76 (5): 940–55.
- Griliches, Z. 1990. *Patent Statistics as Economic Indicators: A Survey*. 28 (4).
- Hall, Bronwyn H., Zvi Griliches, and Jerry A. Hausman. 1986. *Patents and R&D: Is There a Lag?* 27 (2).
- Hall, Bronwyn H, and Dietmar Harhoff. 2012. ‘Recent Research on the Economics of Patents’. *Annual Review of Economics* 4 (1): 541–65.
<https://doi.org/10.1146/annurev-economics-080511-110911>.
- Hall, Bronwyn H, Christian Helmers, Mark Rogers, and Vania Sena. 2012. *The Choice between Formal and Informal Intellectual Property: A Literature Review*. NBER

Working Paper Series. National Bureau of Economic Research.

- Hall, Bronwyn H., and Rosemarie Ziedonis. 2001. *The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor*. 32 (1).
- Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2005. 'Market Value and Patent Citations'. *Wiley-Blackwell* 36 (1).
- Hausman, Jerry A., Bronwyn H. Hall, and Zvi Griliches. 1984a. 'Econometric Models for Count Data with an Application to the Patents-R & D Relationship'. *Econometrica* 52 (4): 909–38. <https://doi.org/10.2307/1911191>.
- Hausman, Jerry A., Bronwyn H. Hall, and Zvi Griliches. 1984b. 'Econometric Models for Count Data with an Application to the Patents-R&D Relationship'. *National Bureau of Economic Research (NBER)*, NBER Working Paper No. 1455.
- Hayes, Vic, and Wolter Lemstra. 2009. 'Licence-Exempt: The Emergence of Wi-Fi'. *Info* 11 (5): 57–71. <https://doi.org/10.1108/14636690910989333>.
- Jaffe, Adam B., Manuel Trjtenberg, and Rebecca Henderson. 1993. 'Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations'. *Oxford University Press* 108 (3).
- Kaplan, Edward L., and Paul Meier. 1958. 'Nonparametric Estimation from Incomplete Observations'. *Journal of the American Statistical Association* 53 (282).
- Kiefer, Nicholas M. 1988. 'Economic Duration Data and Hazard Functions'. *Journal of Economic Literature* 26.
- Kortum, Samuel, and Josh Lerner. 1999. *What Is behind the Recent Surge in Patenting?* 28 (1): 1–22.
- Lemley, Mark A., and Carl Shapiro. 2007. *Patent Holdup and Royalty Stacking*.
- Lerner, Josh, and Jean Tirole. 2004. 'Efficient Patent Pools'. *American Economic Association* 94 (3): 691–711.
- Levin, Richard C., Alvin K. Klevorick, Richard R. Nelson, and Sidney G. Winter. 1987. 'Appropriating the Returns from Industrial Research and Development'. *Brookings Institution Press*, Brookings Papers on Economic Activity. Microeconomics, 783–831.
- Machlup, Fritz, and Edith Penrose. 1950. 'The Patent Controversy in the Nineteenth Century'. *Cambridge University Press* 10 (1): 1–29. <https://doi.org/10.1017/S0022050700053155>.
- Negus, Kevin J, and Al Petrick. 2009. 'History of Wireless Local Area Networks (WLANs) in the Unlicensed Bands'. *Info* 11 (5): 36–56. <https://doi.org/10.1108/14636690910989324>.
- Oh, Sarah. 2020. 'Radio "Fences" and Inventor Attention to Property Rights: Evidence from Wireless Patents'. *Review of Industrial Organization* 56 (1): 37–72.

<https://doi.org/10.1007/s11151-018-9665-5>.

- Pakes, Ariel, and Zvi Griliches. 1980. *Patents and R&D at the Firm Level: A First Look*. 5 (4).
- Reinganum, Jennifer F. 1989. 'The Timing of Innovation: Research, Development, and Diffusion'. In *Handbook of Industrial Organization*, vol. 1. Elsevier Science Publishers.
- Scotchmer, Suzanne. 1991. 'Standing on the Shoulders of Giants: Cumulative Research and the Patent Law'. *American Economic Association* 5 (1): 29–41. <https://doi.org/10.1257/jep.5.1.29>.
- Scotchmer, Suzanne. 2005. *Innovation and Incentives*. MIT Press.
- Shapiro, Carl. 2001. 'Navigating the Patent Thicket'. In *Innovation Policy and the Economy*. MIT Press.
- Trajtenberg, Manuel. 1990. 'A Penny for Your Quotes: Patent Citations and the Value of Innovations'. *RAND Journal of Economics* 21 (1). <https://doi.org/10.2307/2555502>.
- Trajtenberg, Manuel, Adam B. Jaffe, and Rebecca Henderson. 1993. 'Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations'. *Oxford University Press* 108 (3).
- Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. MIT Press.
- Ziedonis, Rosemarie Ham. 2004. *Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms*. 50 (6): 804–20.

APPENDIX

Table A.1 – Robust Standard Error Results from Table 4.1

Variables	Poisson (1)	Poisson (2) + Sector FE	Poisson (3) + History
Avg. IPC number	0.541319	0.72593	0.0759292
Avg. inventor count	0.2311815	0.3729974	0.3915281
Entry year	—	—	0.0076652
Foundation year	—	—	0.0036583
Sector FE	No	Yes	Yes
Consumer Electronics & Digital Entertainment		0.6321219	0.627997
Semiconductors & Electronic Components		0.1234033	0.1285227
IT, Software, and Cybersecurity		0.0373197	0.0387186
Automotive & Industrial Electronics		0.1033206	0.0991129

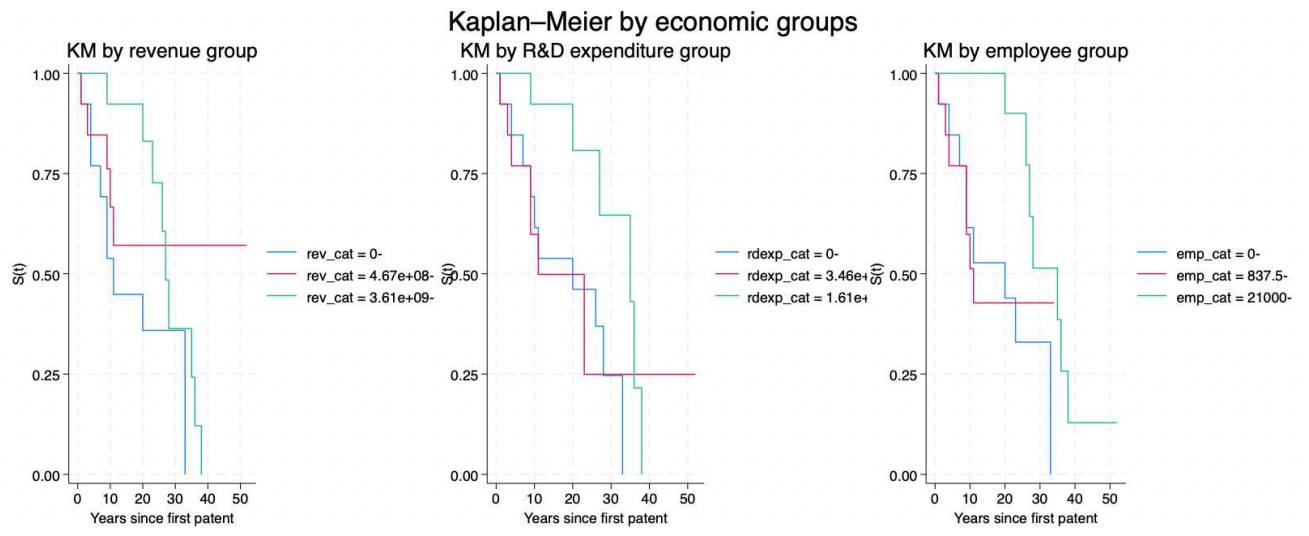


Figure A.1 – Non-parametric Results by splitting the Sample by Terciles of Revenues, R&D Expenditure, and Employees