Determinants of Innovation: An Evidence-Based Perspective in the Digital Transformation Era

by
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Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Science Engineering and Technology

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Declaration

I, Saltanat Akhmadi, declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the author’s original work. The thesis has not been previously submitted to this or any other university for a degree and does not incorporate any material already submitted for a degree.

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Date: March 5, 2023

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Abstract

Innovation, the process of finding and using new ideas, creating new products or services, and introducing them to the market, is widely celebrated as the driving force of economic growth, sustainable development, and social change. Yet, innovation activity around the world is mostly concentrated in a few leading countries that possess the human and financial capital to create new knowledge and the market acumen to capitalize on it. For instance, three quarters of the patent filings from global innovation hotspots are emerging from just four countries – USA, Japan, China, and Germany.

This uneven concentration of inventive activity, aptly named the global innovation divide, increases the gap between developed and developing economies. The situation has exacerbated over the last decade with the fourth industrial revolution and the emergence of the digital economy that has brought to the forefront knowledge generation and utilization. To close the innovation gap, regional, national, and international governments and authorities constantly encourage innovation through an array of fiscal subsidies and regulatory interventions with admittedly mixed results.

Innovation of course starts at the firm level, with innovative firms developing competitive advantages for themselves and for their regions through knowledge exploration and exploitation and the creation of new technologies. Even in innovation leaders such as Germany, roughly one in two enterprises do not engage in innovation. Obstacles to innovation reflect the realization that innovation is a difficult, financially risky, and mostly liable to fail process. A multitude of business surveys and research studies have been dedicated to identifying and assessing the importance of the obstacles that deter firms from innovating and contrasting them with the obstacles slowing down, but not stopping, firms already engaged in innovation. While there is a broad consensus on what constitutes an obstacle to innovation, the term is open to a wide range of interpretations that are largely contingent upon the context within which innovation occurs. This handicaps the effectiveness of innovation policies that are based upon a generic understanding of the innovation process and are not sufficiently nuanced for the digital era.

Past research on innovation has sought to identify major correlates of innovation by assessing only one dimension of innovative behavior at each time. Treating the phenomenon of innovation as unidimensional does not sufficiently capture the richness of the construct of organizational innovation. This dissertation demonstrates instead that the process of innovation is decidedly multi-dimensional and explores the multi-faceted nature of the impact of innovation on firms, regions, and countries. Based on an extensive range of

publicly available datasets and using a multi-dimensional analytical approach, this dissertation dissects the phenomenon of innovation at several layers of abstraction: the firm layer, the operational layer, the process layer and the policy layer. The contributions of this dissertation at each layer are addressed in turn.

- At the firm layer, the key characteristics of the profile of an organization that impact its involvement in innovation activities are identified as firm size, sector, and prior engagement in innovation activities.
- At the operational layer, the effect of factors present in the operational environment within which innovation occurs is measured with emphasis on economic, market, cultural and gender diversity issues.
- At the process layer, issues related to knowledge acquisition, elicitation, and management in innovative firms are introduced and examined in the context of tangible innovation outputs such as intellectual property rights.
- At the policy layer, the effect of innovation policies and interventions over the last decade is assessed with a special focus on the promotion of clustering activities and innovation hotspots.

The results of this evidence-based dissertation presented herein are instrumental in defining the specific facets of an effective, modern innovation policy, producing the desired performance outcomes in a context of limited resources for innovation.

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EU	European Union
WIPO	World Intellectual Property Organization
GII	Global Innovation Index
CIS	Community Innovation Survey
EFTA	European Free Trade Agreement
IPRs	Intellectual property rights
NLPM	Nonlinear probability model
NACE Rev. 2	Statistical classification of economic activities in the European Community
PCT	Patent Cooperation Treaty
PROs	Public research organizations
MCDA	Multi-criteria decision analysis
SML	Firms with 10 to 49 employees
MED	Firms with 50 to 249 employees
LRG	Firms with more than 250 employees
PROD	Firms operating in production activities
SERV	Firms operating in service activities
MEMs	Marginal effects at the means
MERs	Marginal effects at representative values
AMEs	Average marginal effects
APMs	Adjusted predictions at the means
APRs	Adjusted predictions at representative values
AAPs	Average adjusted predictions
LFIN_IN	Lack of internal finance
LFIN_EXT	Lack of external finance (credit or private equity)
H_COST	High costs of innovations
L_SUBS	Difficulties in obtaining public grants or subsidies
U_DMND	Uncertain market demand for innovations
H_COMP	High competition in the relevant market
L_EMPL	Lack of qualified employees within the firm
L_PRTN	Lack of collaboration partners
L_EXTKN	Lack of access to external knowledge
NON-INNO	Firms not engaged in innovation

INNO	Firms engaged in innovation
CIS2014	Survey conducted in 2012-2014
CIS2016	Survey conducted in 2014-2016
CIS2018	Survey conducted in 2016-2018
CIS2020	Survey conducted in 2018-2020
DE	Germany
PL	Poland
PT	Portugal
MK	North Macedonia
IT	Italy
FI	Finland
EE	Estonia
RO	Romania
GROUP	Enterprises within the enterprise group
SUPPL	Suppliers of equipment, materials, components or software
PRIVT	Clients or customers from the private sector
PUBLC	Clients or customers from the public sector
COMPT	Competitors or other enterprises of the same sector
CONSLT	Consultants or commercial labs
UNIVS	Universities or other higher education institutions
GOVRN	Government or public research institutes
RESIN	Private research institutes
FAIRS	Conferences, trade fairs or exhibitions
PRINT	Scientific/technical journals or trade publications
ASSOC	Professional or industry associations
INT_RD	R&D activities undertaken by the firm to create new knowledge, including software development in-house that meets this requirement
EXT_RD	R&D activities contracted to other firms (include enterprises in the same group) or to public or private research organizations
EXT_KN	Acquisition of existing know-how, copyrighted works, patented and non-patented inventions, etc. from other firms or organizations
MANUFG	Firms operating in manufacturing sector
INFOCOM	Firms operating in information & communication sectors
SMEs	Small and medium enterprises

PCTF	Total number of PCT filings
WI	Share of women inventors
POP	Total population of the geographical area
USPTO	USA Patent and Trademark Office
DOM	Share of top entity filings
SPE	Share of top sector filings
PRO	Share of total PROs filings
VIF	Variance inflation factor
GERD	Gross domestic expenditure on R&D
KMG	KazMunayGaz
NCOC	North Caspian Operating Company
NCSPSA	North Caspian Sea Production Sharing Agreement
TCO	TengizChevrOil
IPC	International Patent Classification
EE	Electrical engineering
IN	Instruments
CH	Chemistry
ME	Mechanical engineering
OF	Other fields

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1. Introduction

1.1. Background and motivation

Innovation, the process of finding and using new ideas, creating new products or services, and introducing them to the market, is widely celebrated as the driving force of economic growth, sustainable development, and social change. Innovation increases competitiveness and operational efficiency from individual firms to entire industries and boosts the growth and development of the regions and counties in which they operate.

Although everyone is in favor of innovation, innovation output around the world is mostly concentrated in very few economies that possess simultaneously the critical complementary factors of requisite skills, knowledge, and market acumen to capitalize on emerging technologies. For instance, 77% of the patent filings from global innovation hotspots are emerging from just four countries – USA, Japan, China, and Germany [1].

This asymmetry, often referred to as the innovation gap, can be also observed across firms operating in the same economy. For instance, in innovation-leading Germany about one out of three firms surveyed declared themselves as non-innovative. Across the European Union (EU) economic space, involving about 30 countries, roughly one out of two firms surveyed stated that they are not involved in innovation activities [2].

The very real phenomenon of the innovation gap has generated several legitimate questions on how well the process of innovation is understood and several hypotheses have been put forward to explain its origin [3,4]. Ultimately though these hypotheses, and the innovation policies they led to, failed to ameliorate the situation, making it apparent that the innovation process is a multi-dimensional construct the facets of which have not been fully identified or understood.

Regional, national, and international governments and authorities have launched numerous innovation campaigns to support and promote innovation activities and to close the innovation gap. These campaigns, aiming to encourage a wider focus on innovation, have been operating systematically for the better part of the last three decades.

However, most of these campaigns became recurrent and highly anticipated interventions targeting one or two issues of local significance, without further coordination within the context of a broad innovation policy. The importance of these campaigns came recently under critical review that focused on their apparent failure to achieve stated targets [5,6]. In fact, after numerous reviews of the issue, there is very weak empirical evidence to support the effectiveness of such innovation policies and their resultant interventions [7,8]. The example of innovation-leader Germany is again characteristic.

The World Intellectual Property Organization (WIPO) compiles every year a list of innovation metrics across more than 132 economies worldwide [9]. These metrics purport to measure both the effort expended on innovative activities ("*inputs*") as well as the perceived outcomes ("*outputs*") in an economy, resulting in a total score aptly named the Global Innovation Index (GII). Figure 1 depicts the composite innovation input and output indices for Germany across the last decade. Surprisingly, there is practically no correlation between the input and output indices -in fact, the negligible correlation that exists is negative (r = -0.24).

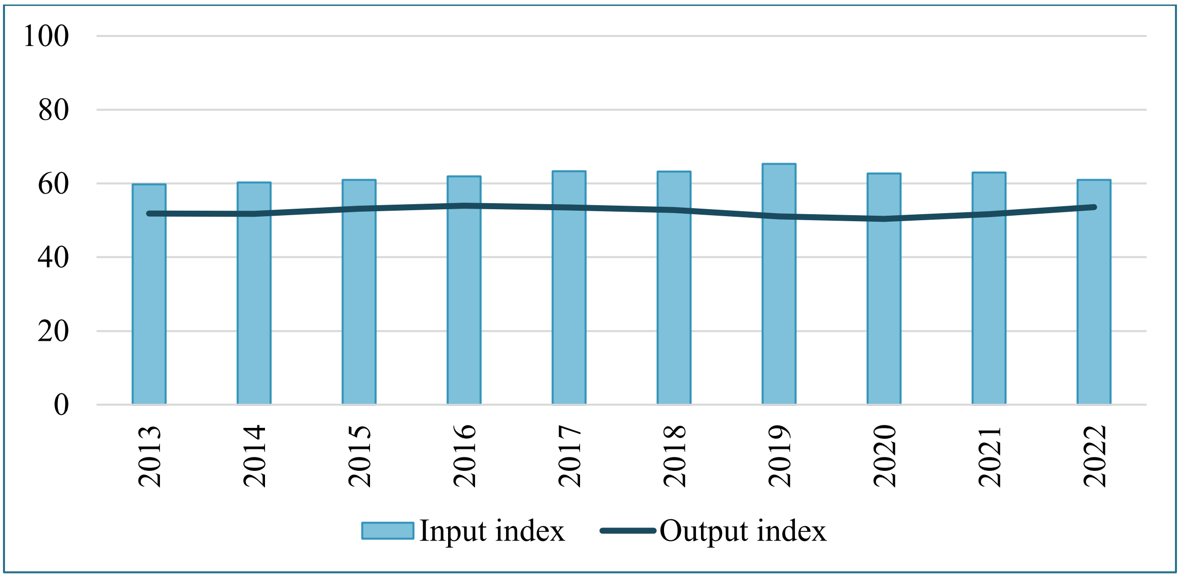


Figure 1. Global Innovation Index, Germany.

Similar patterns can be observed over a large swath of countries worldwide. The dissociation between policies supporting innovation and innovation outputs signals that even elaborate constructs such as the GII fail to capture important aspects of the innovation process.

As the world is in dire need of effective policy interventions to close the innovation gap, there is a new sense of urgency. *Digital transformation* -the integration of digital technology into all areas of a business- is fundamentally changing how firms operate and deliver value to their customers. It is also a *cultural* change that employs fundamental tenets of the innovative mind (challenge the status quo, dare to experiment, and get comfortable with failure). Furthermore, digital transformation appears to widen the gap between developing and developed economies and to handicap the implementation of the United Nations 2030 Sustainable Development Agenda [10].

It is thus imperative to study the process of innovation from new, vantage points that exploit the wealth of information collected over the past decade of monitoring innovation around the world. The motivation for this thesis is to study the process of innovation at several levels of abstraction to understand better this admittedly multidimensional phenomenon [11,12]. The objective is to explore the *determinants* of innovation, the elements that identify or determine the nature of innovation as defined in [13].

The fundamental question posed in this thesis is to identify what inhibits firms (and indeed regions and countries) from innovating and to provide a nuanced, evidence-based view of the obstacles involved.

The novelty of this thesis lies in its exploration of the innovation process both from the point of view of the individual firm and its characteristics and from the point of view of the country the firm operates and its economic, social and cultural environment. Furthermore, the thesis introduces the concept of innovation as a *dynamic* process and examines the variable of time to study the evolution of the issues involved over the span of a decade.

Finally, this thesis introduces for the first time some heretofore unexamined qualifiers of the innovation process such as the concept of clustering, the issue of gender and diversity and the socio-cultural element.

1.2. Research design

With the fundamental question and the research objectives set in the previous section, the research design of this thesis was based on the strategic choice to ground the study on rich enough datasets. It was thus decided to avoid questionnaire analysis of limited samples but to proceed with publicly available data of sufficient size and depth to guarantee both: (i) a high level of confidence in the significance of the outcomes of the analysis; and (ii) the reproducibility of such outcomes for comparative purposes or future research.

For instance, the aforementioned WIPO data from the construction of the GII for 132 countries were employed to obtain evidence for country-level analysis, and to explore issues such as business clusters and industrial networks, gender diversity and its impact on innovation performance or even to question the efficacy of the GII itself in capturing innovation output.

Similarly, the Community Innovation Surveys (CIS) by Eurostat of over 600,000 firms in the European Free Trade Agreement (EFTA) countries as well in member and candidate states of the EU provide a rich tapestry of innovation over the years and across the firms. CIS data were employed to assess the innovativeness of different firms, sectors, and regions [2].

While the use of such publicly available and officially vetted datasets satisfied the strategic choices of the thesis set forth earlier, there were issues and limitations. The CIS data are collected biannually by the national statistical offices of over 30 countries and are then compiled by Eurostat in a process that is meticulous and thus lengthy. Typically, the public data release normally takes place two and half years after the end of the survey reference period. The survey template has remained more or less stable over the years, yet there are some distinct differences between surveys that complicate comparisons over time. In addition, individual countries often fail to report data on specific issues further complicating comparisons. The analysis in this thesis proceeded despite such limitations, which are clearly noted and discussed in the corresponding sections.

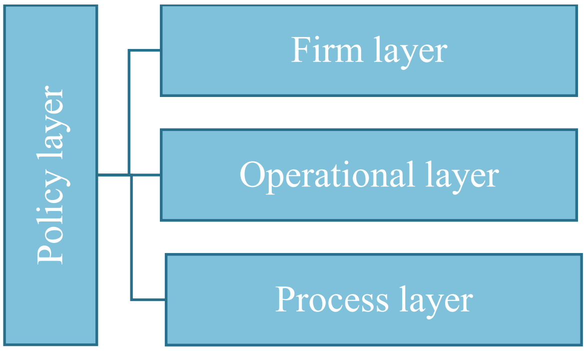


Figure 2. Four-tier conceptual architecture.

The development of the thesis is based on a conceptual four-tier architecture of innovation the characteristics of which are depicted in Figure 2. This novel schema, which is a contribution of the thesis, provides for a succinct organizational framework of the queries posed to the available datasets and can be useful for the standardization of similar studies.

Specifically,

- At the *firm layer*, queries are related to the key characteristics of the profile of an organization that impact its innovativeness, such as firm size, sector, and prior engagement in innovation activities.

- At the *operational layer*, queries are related to factors present in the operational environment within which innovation occurs, with emphasis on economic, market, cultural and gender diversity issues.
- At the *process layer*, issues related to knowledge acquisition, elicitation, and management in innovative firms are introduced and examined in the context of tangible innovation outputs, such as intellectual property rights (IPRs).
- At the *policy layer*, the effect of innovation policies and interventions over the last decade is assessed with a special focus on the promotion of clustering activities and innovation hotspots.

Every layer of the four-tier architecture in Figure 2 can be updated or expanded individually. The architecture does not presume a hierarchy or a dependency among the layers, other than the notion that policy interventions can, in principle, impact firm, operational and process issues. This four-tier architecture put forward is not a functional model of innovation; rather it is a construct aiming to organize distinct dimensions of innovation across a limited number of thematic axes. The queries addressed in this thesis are organized based on the four-tier architecture in Figure 2.

A key tenet of the research on innovation is that there are specific factors inhibiting innovation and the impact of which policy interventions aim to ameliorate. These factors, often referred to as obstacles or barriers to innovation, reflect the realization that innovation is a difficult, financially risky, and mostly liable to fail process. While there are different taxonomies of the obstacles to innovation, the analysis in this thesis is based on the classification introduced largely by the CIS which assesses 10 specific obstacles in its latest editions.

The CIS data record the relative importance of these obstacles at the firm level, painstakingly tabulated to reflect firm size, sector of operation, and innovativeness along with a slew of other data. The publicly available data [2] are presented in a form that is not directly conducive to analysis and various attempts have been made in the past to tabulate them in a form that can be amenable to statistical analysis [14]. This thesis moves a step forward and presents a novel way of agglomerating the data that facilitates their analysis and guarantees the reproducibility of the results now and in the future by providing a set of methodological rules for the agglomeration.

Furthermore, considering the specific polling system employed by Eurostat and its constituent national statistical agencies, a Probit-based analytical instrument was developed to enable a standardized level of analysis using the STATA software.

An important caveat of the CIS (but not of the WIPO) data is that they reflect perceptions about innovation. It has been established that perceptions impact innovation performance and, at the same time, innovation performance is a key determinant of established perceptions [15]. A workaround to this circular argument is to differentiate the opinions of firms actively engaged in innovation (reporting on obstacles they faced in the process) from those of firms not engaged in innovation (which reflect only perceived or anticipated difficulties). In addition, the sheer size of the CIS dataset (encompassing more than 600,000 firms in each release) is expected to allow for the recognition of major trends in the data, that is of firmly entrenched opinions on the issues related to innovation.

Finally, the queries posed in the process of the analysis are by necessity confined to the firms, sectors and countries for which sufficient data exists. Innovation-leader Germany figures prominently in the analysis, but care is exercised -to the extent possible- to compare and contrast its data with those of countries with varied social, economic and developmental profiles.

1.3. Thesis organization

Within this general context, the thesis is organized as follows. A concise literature review is presented in Chapter 2. The question of what exactly impedes innovation has been examined exhaustively by government and industry think tanks, by consulting firms and by academic researchers [16–19]. The systematic review of the literature in Chapter 2 reveals that the classification of obstacles to innovation has evolved over the years from the elementary characterization of obstacles as internal or external to the firm to the now universally accepted taxonomy of the CIS methodology.

While the CIS schema is adopted explicitly in this thesis, the historical narrative is needed to provide a more nuanced understanding of the issues involved and, ultimately, of the proposed clustering of the 10 CIS obstacles into three major thematic categories defined as *finance*, *market* and *knowledge.* This clustering serves in effect as a "noise-reduction" filter in the processing of the data and helps in the recognition of major trends [20].

The 10 obstacles to innovation of the CIS schema play the role of *dependent variables* in the architecture of Figure 2. The raw country-level CIS data, however, include a lot of detailed information regarding the size, sector, and innovativeness of the firms surveyed along with a slew of other factors and information. The situation is complicated by the fact that the firms surveyed were polled with a four-tier Likert scale, yet the data put forward by

Eurostat tabulate are in binary form, recording only the number of firms that have a very definite position -positive or negative- on each obstacle. The publicly presented format of CIS results is not directly amenable to in-depth statistical analysis, requiring extensive cleaning and pre-processing of the tabulated data. In Chapter 3, building upon early attempts to streamline the process [14], this thesis sets forth a meticulously researched and carefully calibrated format that allows for the use of sophisticated statistical analysis algorithms and safeguards reproducibility.

In Chapter 4, the issues related to the analysis are discussed at length and the proposed methodology is detailed. It is common practice in innovation research to employ regression analysis. Considering that the CIS data format leads in effect to categorical, and often binary, variables it should be appreciated that in such cases regression models produce nonlinearities in the predicted probability metrics. A variant often employed is to use a nonlinear probability model (NLPM), that is a regression model that employs a nonlinear transformation to become linear in its parameters. The clear favorite in innovation studies is *Probit*, an NLPM that effectively models the probability of a dichotomous or binary outcome as a linear combination of categorical predictors [21–24]. Probit is indeed adopted in this thesis, but with a novel twist. Instead of developing predictive models, an alternative metric -called *marginal effects*- is employed to understand how the value of an independent variable in Probit changes with a unit change in one of the regressor variables. This choice facilitates interpretation and is uniformly used in the analysis throughout this thesis.

With the dependent variables, the pre-processing of the data and the regression methodology defined, the study proceeds to the *firm layer* in Chapter 5. The benchmarking example is innovation-leader Germany, representing more than 100,000 firms in the CIS surveys. Germany is the "darling" of innovation research, not only because of its rich tapestry firms of all sizes operating across all forms of enterprise, but also because the country systematically reports in the CIS the self-categorization of its companies as innovative or non-innovative, allowing for the control of one more important discriminant during the analysis. The data of Germany are analyzed for the 8 obstacles of the CIS 2016 edition, with the regressors being the *independent variables* of firm size class (small, medium, or large), sector of operation (production or services) and innovativeness (engaged or not in innovation). This painstaking analysis addresses key unresolved issues such as the relationship between firm size and innovativeness. Indeed, Schumpeter's hypothesis that only large companies can support the costs related to innovation, has neither been confirmed nor rejected and remains a puzzle [25–27].

The results in Chapter 5 demonstrate succinctly that firm size matters when examining the relative importance of the various barriers to innovation. Furthermore, it is shown that such importance is significantly moderated by whether a firm has been involved or not in innovation activities [28]. As the results obtained reflect only the situation in Germany, the analysis in Chapter 5 is augmented by a similar analysis at the firm layer of firms operating in a host of countries with different socio-economic, cultural and innovativeness levels. The results obtained for Italy, Poland, Portugal, Finland, Estonia, Romania, and North Macedonia do confirm the main trends identified for Germany.

In Chapter 6, the focus shifts to the *operational layer,* that is the socio-economic environment in which a firm operates. Several tenets have appeared in the literature postulating that social and cultural differences may be behind the innovation gap. Within the broader EU, Central and Eastern European countries persistently lag in innovation rankings compared to their Western Europe counterparts [29]. The existence of cultural barriers to innovation has been offered as an explanation for this lag, on the premise that a top-down, hierarchical culture that induces fear of consequences and thus neutralizes curiosity can be detrimental to innovation [30]. The analysis in this chapter examines whether the CIS data supports the existence of divergent perceptions of innovation between firms operating in the East and the West. A set of four countries with distinct socio-economic profiles (Germany, Poland, Portugal and North Macedonia) for which innovation data of sufficient granularity exist is used to demonstrate that there is no discernible East-West cultural divide but rather a palette of shades regarding perceptions of innovation, entrenched in firm-level characteristics. Specifically, firm size colors perceptions of innovation and in turn such perceptions moderate the inclination to innovate much more heavily than cultural issues [31].

Similar arguments have been advanced about the level of development of the country in which a firm operates, and whether it belongs to the “Global North” or the “Global South”, that is the list of countries whose economies are not yet fully developed, and which face specific socio-economic challenges [32]. The current digital transformation, that is the adoption and integration of digital technologies into all areas of business, is the key developmental axis as innovation activities are its core. Unfortunately, there is a paucity of data on this issue other than a rudimentary scoring of countries on a few assessment indexes [33]. Chapter 6 includes a small exploratory study using primary data collected in Kazakhstan, a Global South country, and an exemplar of post-Soviet Central Asia. Interestingly, the analysis reveals that the most important facet of digital development vis a vis innovation is the gender digital level, that is the inequality in access to digital resources across gender. This outcome correlates well with the observation that countries categorized as high-income report the highest levels of equal digital access, whereas low-income countries report the lowest [33] but will require future verification on a grander scale.

Chapter 7 centers on the *process layer*, that is on issues directly related to the actual process of innovation, with the analysis shifting away from perceptions about innovation to tangible innovation outputs, such as IPRs. The first part of the chapter deals with the process of knowledge acquisition and management in innovative firms. Innovative firms develop competitive advantages through knowledge acquired externally or developed internally, and its management, exploration, and exploitation. By focusing on a sample of 36,000 German innovative firms for which knowledge sourcing and innovation expenditures are recorded in the CIS datasets, it emerges that these firms depend mostly on internal sources (including enterprises within the enterprise group) and to a much lesser extent on market sources (primarily clients or customers from the private sector). This outcome is further amplified by the fact that the lion's share of innovation expenditures is devoted to internal R&D with very limited resources targeting external contract research or outright acquisition of knowledge from third parties.

This emphasis on the firm and its internal resources for innovation led to a re-examination of two key themes that were studied in Chapters 5 and 6. The issue of innovation propensity and firm size is revisited from the point of view of actual IPRs produced, from patents and trademarks to trade secrets and copyrights. Using a sample of 63,000 German manufacturing firms for which comprehensive IPRs data exist in the CIS datasets, it is determined that firm size does affect innovation output. Indeed, large firms appear to have an innovation advantage in that innovation, with its high fixed costs and inherent risks, is better suited for economies of scale which only large firms can exploit. In this context, most small- to medium-size firms remain technology followers. This outcome amplifies better the observation that firm size matters which emerged in the study of Chapter 5 and creates an argument for the adoption of IPRs as a better reflection of the situation than the surveys of perceptions about innovation in the bulk of the CIS data.

Finally, Chapter 7 concludes with a more in-depth examination of the gender issue that was observed in the Kazakhstan study of Chapter 6. Gender diversity is purported to be critical for innovation success, yet scant empirical evidence exists to support this claim. The paucity of data-driven studies on the linkage between diversity and innovation is because innovators are almost invisible in innovation research, in sharp contrast to entrepreneurs who figure prominently in entrepreneurship studies. The study put forward in this chapter examines the issue of gender in innovation through an analysis of patent application data from geographical regions with intense innovative activity. Patent application data are a direct -although not fully complete- metric of innovation output as they mostly capture technological innovations. A comprehensive analysis of the 31 top innovation hotspots in the USA based on WIPO data reveals that the percentage of women innovators is weakly correlated with the total patent output of innovation hotspots. While the correlation does not appear to be statistically significant, further equivalency tests suggest that the admittedly small effect is not negligible. The results of this exploratory study thus set the stage for a more comprehensive one that will have to be designed with a richer set of data.

Chapter 8 focuses on the policy layer and the perceived impact of policy interventions in support of innovation such as industrial clustering or innovation campaigns. Industrial clusters are examples of economic agglomeration, the tendency that is of firms in a particular field to concentrate geographically to achieve economies of scale and scope. The industrial cluster concept has grasped the imagination of policymakers and proved extremely popular with governments eager to develop policies to promote innovation. Even though it has not been conclusively proven that clusters invariably boost business performance and local development [34–36], the popularity of the cluster concept amongst policymakers remains intact. By data mining over 950,000 patent applications filed over the four-year period 2011-2015, WIPO identified the world's top-100 innovation clusters based on their patent activity [37]. The resultant dataset provides information on cluster performance within and across countries in a systematic, data-driven way. The analysis in this chapter demonstrates that more loosely organized clusters tend to be more patent-productive and that the involvement of universities and public research institutions may be an impediment to patent productivity. Considering that public policy interventions typically aim to create well-defined clusters and often require the participation of universities and other public research entities, this can be counterproductive to tangible innovation output. Once again, the analysis in this thesis provides additional support for the adoption of IPRs as better innovation metrics instead of perception surveys.

It can be hypothesized of course that policy interventions may have a delay in producing tangible results. The analysis of large-scale data from Europe demonstrates that promoting innovation succeeded in reducing the perceived importance of financial, market and knowledge barriers of innovation [38]. Yet, promoting innovation did not have any major effect in changing the actual number of innovative firms in Europe with the notable exception of Italy [38]. Considering that Italy is the only country in the CIS for which consistent data exist over the span of a decade, a longitudinal study was performed to understand the successful characteristics of its public innovation policy. The evidence-based findings in Chapter 8 demonstrate succinctly that effective innovation campaigns augment financial and market incentives with a targeted emphasis on improving skills and digital competencies in the workforce.

Finally, in Chapter 9, a summary of the conclusions and recommendations of the thesis is presented along with a delineation of the contributions and suggestions for future research.

1.4. Summary and conclusions

The objective of this thesis was to examine the process of innovation and to develop evidence-based insight into what inhibits non-innovative firms from innovating and into what is important for innovative firms in their drive to excel. The thesis brings forward new vantage points of the phenomenon of innovation by using large-scale, publicly available data. Indeed, the major novelty of the thesis is the introduction of several levels of abstraction in the exploration of the multi-faceted phenomenon of innovation.

The key contributions of the thesis include:

- the recognition of the fundamental importance of *firm size* in everything related to innovation, supported by studies employing perception surveys as well as actual IPRs produced;
- the understanding that innovative firms to a large extent look *internally* to develop the knowledge needed for innovation and devote accordingly the lion's share of their innovation expenditures to internal R&D;
- the emergence of *human capital*, and in particular *gender diversity*, as an integral part of successful innovation in the digital era;
- the apparent *ineffectiveness* of certain aspects of broad-based public policy campaigns in support of innovation; and
- the effective demonstration of innovation as a *dynamic* process across the continuum of time.

Admittedly, the studies from which these outcomes emerged are limited by the paucity of reliable and consistent data. Indeed, the exploratory studies in this thesis set the stage for future research and pose key questions on the efficacy of innovation indicators collected and the metrics employed worldwide.

With this caveat in mind, the key outcomes of the thesis, and several other relevant corollaries that emerged, are expected to drive the development of new and more nuanced government policies and the implementation of targeted interventions in support of innovation.

2. Obstacles to innovation

2.1. A historical perspective

From the early 1960s, there were attempts to identify what impedes innovation. The earliest studies focused on the main factors affecting innovation in various fields and contexts, from technology [39] and public health [40] to education [41,42] and venture capitals [43,44]. It should be noted that the terms “obstacles” or “barriers” to innovation were not that common in that era and many authors addressed them simply as “causes of failure” [44].

The list of the obstacles identified in that period ranged from underestimation of competition and selling effort to bandwagon effect and “espousal of traditional values”. While the peculiarities of the individual fields inevitably lead to the cases when some authors tended to address specific factors and barriers, some common factors emerged across this variety of studies. For instance, [39] highlighted five factors affecting innovation:

- Research and development activity;
- Purchase and flow of knowledge;
- Talent;
- Economic and market structure; and
- Investment and availability of financing.

Similar terms reappeared in later studies, gradually evolving into technological, economical, organizational, and personnel-related obstacles [42].

The studies from the 1980s were marked by more comprehensive and structured approach to the analysis of innovation barriers (such as [45,46] based on the postal surveys among manufacturing firms in USA and Netherlands respectively). The authors addressed new relevant issues like corporate support, unrealistic expectations, inadequate planning and operational difficulties [47]. Some authors also introduced more modern formulations of the obstacles to innovation like difficulties with finding technical information, lack of highly qualified engineers and technicians, management structure, difficulties in forecasting market demand, lack of capital, too high expected costs of innovation, and others.

The view from the field continued to coalesce around common themes with the emergence of CIS in the early 1990s. CIS emerged as a response to the shared need of researchers and policymakers for direct and country-wide indicators of innovation at the firm level. Indeed, CIS was and is the largest innovation survey in the world based on the number of participating countries and the number of responding enterprises. Although the data collected covers EU members and candidate countries, CIS has influenced the design of innovation surveys around the world [48].

The initial survey (CIS 1992) was a pilot one of limited release. The full complement of the survey was launched in CIS 1996 and was expected to be quadrennial but it became biennial after CIS 2004. Each CIS covered a broad range of innovation topics with special topics added to individual surveys (Table 1).

Table 1. CIS: Broad scope of topics*.

CIS	Innovation topics	Special topics
1992	Information sources, objectives, obstacles, IPRs, sales	Technology acquisition/transfer
1996	Information sources, objectives, obstacles	
2000	Information sources, effects, obstacles, IPRs	Patenting
2004	Information sources, effects, obstacles, IPRs	
2006	Information sources, effects, obstacles, IPRs	
2008	Information sources, objectives	Environmental innovation
2010	Information sources, objectives, obstacles	Creativity and skills
2012	Information sources, obstacles, IPRs	Firm objectives and strategies
2014	Public procurement, obstacles, IPRs	Environmental innovation
2016	Information sources, activities, obstacles, legislation, IPRs	Innovation in logistics
2018	Financing, obstacles, legislation, IPRs	Knowledge flows
2020	Financing, obstacles, legislation, IPRs	Not released completely yet

* *adapted from* [49]

The obstacles to innovation have been central to the CIS occupying a prominent position in most surveys. Over the years, there have been both minor and substantive changes to the questions posed in an effort to improve data quality and to facilitate interpretation. While many obstacles remained on the list throughout this period, new factors (potential topical barriers) were added or existing (perhaps outdated ones) were extracted as the surveyors implicitly recognized the dynamic nature of innovation barriers. Interestingly, some of the extracted obstacles were then re-introduced into the list (mostly in CIS 2014).

Thereby, Table 2 summarizes the obstacles (with their exact label) in CIS releases. Highlighting the dynamic nature of the obstacles' appearance in the surveys it can be observed that a barrier reflecting the issues with competition was introduced only in CIS 2004 and appeared until CIS 2010 as Markets dominated by established enterprises.

Table 2. Distribution of the obstacles to innovation in CIS releases.

1996	2000	2004, 2006	2010	2012	2014	2016	2018, 2020
Lack of appropriate sources of finance	Sources of finance	Lack of funds within the enterprise or group Lack of internal finance	Lack of funds within the enterprise or group Lack of finance from sources outside the enterprise	Lack of adequate finance	Lack of internal finance* Lack of external finance (credit or private equity) * Difficulties in obtaining public grants or subsidies*	Lack of internal finance Lack of external finance (credit or private equity) Difficulties in obtaining public grants or subsidies	Lack of internal finance Lack of external finance (credit or private equity) Difficulties in obtaining public grants or subsidies
		Markets dominated by established enterprises	Markets dominated by established enterprises	Innovations introduced by competitors Dominant market share held by competitors Strong price competition Strong competition on product quality		High competition	High competition
						Little market competition*	
Lack of qualified personnel	Lack of skilled employees within enterprise	Lack of qualified personnel	Lack of qualified personnel	Lack of qualified personnel	Lack of skilled employees within enterprise*	Lack of qualified employees within enterprise	Lack of qualified employees within enterprise

1996	2000	2004, 2006	2010	2012	2014	2016	2018, 2020
Too high innovation costs	Innovation costs	Innovation costs too high	Innovation costs too high	High costs of access to new markets High costs of meeting regulations		High costs	High costs
		Difficulty in finding cooperation partners for innovation	Difficulty in finding cooperation partners for innovation		Lack of collaboration partners*	Lack of collaboration partners	Lack of collaboration partners
Lack of information on markets Lack of customers responsiveness	Information on markets Customers responsiveness	Uncertain demand for innovative goods or services Lack of information on markets	Uncertain demand for innovative goods or services Lack of information on markets		Uncertain market demand*	Uncertain market demand	Uncertain market demand
		No need to innovate due to no demand for innovations	No need to innovate due to no demand for innovations	Lack of demand	Low market demand*	Low market demand*	
					Lack of good ideas*	Lack of good ideas*	
		No need to innovate due to prior innovations	No need to innovate due to prior innovations		Previous innovations*	Previous innovations*	
					No compelling reason to innovate*		
Excessive economic risks	Economic risks						

1996	2000	2004, 2006	2010	2012	2014	2016	2018, 2020
Organizational rigidities Problems of regulations fulfilling	Organizational rigidities Regulation and standards						
Lack of information on technology	Information on technology	Lack of information on technology	Lack of information on technology				Lack of access to external knowledge
							Different priorities within the firm

* *reported for non-innovators only*

It was then broken down into four separate obstacles in CIS 2012, which were in turn kept only for one release, and skipped in CIS 2014. The obstacle called High competition was returned only in CIS 2016 and remained on the list thereafter. The dominant list of obstacles appears to have crystallized in CIS releases in 2018 and 2020 reflecting a convergence of views in academic research which has profited immensely from the CIS datasets. Nevertheless, the issue has not been entirely settled and there are divergent views from the business world.

2.2. The business perspective

In parallel with the academic world, consulting firms have also addressed the issue of what impedes innovation and have run rolling surveys for their business clients. In sharp contrast to CIS, these surveys are of a significantly smaller scale but far less impersonal. Typically, they target key stakeholders and executives of major firms and involve in-depth interviews. In that sense, they provide valuable and new, but perhaps less statistically significant, information on the issue.

The most prominent examples are the surveys performed by the international consulting firms of KPMG and Deloitte. These surveys benchmarked innovation impact research by surveying large numbers of executives working in innovation, strategy and R&D and then recording the top-ten obstacles to innovation in terms of the most mentions received in their respective samples. It should be emphasized here that the ranking on the relative importance of obstacles reflects exclusively the opinions of the individuals polled [16,17]. Deloitte [17] surveyed 760 European companies in 16 European countries representing 20 major business fields (Table 3).

Table 3. Obstacles to innovation ranked by Deloitte 2018.

Obstacles to innovation	Votes
Sensing and scanning new technologies and trends	32%
Security issues (data security)	30%
Lack of technical skills	25%
Cultural resistance to risk taking and failing	23%
Lack of leadership and management skills	23%
Uncertain demand for new goods or services	22%
Availability of technology providers to train	22%
Lack of access to funds	21%
Lack of time to develop new ideas	20%
Lack of government support for innovation	16%

KPMG [16] surveyed 215 managers and executives in strategy and R&D, so-called "corporate innovators", thus providing an overview of the perceptions and assessments of the obstacles to innovations from the managerial level of view (Table 4).

Table 4. Obstacles to innovation ranked by KPMG 2020.

Obstacles to innovation	Votes
Politics/Turf-wars/No alignment	52%
Cultural issues	47%
Inability to act on signals critical to future business	42%
Lack budget	40%
Lack strategy, vision	38%
Recruiting/Not enough of high demand skillsets	25%
Not adopting emerging technologies	21%
Lack of executive support	19%
Other	16%
Inability to pick up signals critical to future business	15%

It is an open question of course whether the barriers identified in this way (and their relative rankings) reflect fully or accurately the perceptions of their respective organizations, their staff, and their management. The concern on the representativeness of the top management's opinion was raised in the early 1980s [50]. With this caveat, the results of both studies feature in their top-ten list, almost exclusively, obstacles internal to the organization. Yet, while one can attempt to identify similarities between the two lists it is readily apparent that they are distinct and divergent reflections of the phenomena they seek to capture.

For instance, lack of access to funds for innovation is mentioned only by one in four respondents in the Deloitte study (lending this obstacle an unimpressive rank of 8 out of 10) while lack of budget is mentioned by two in five respondents in the KPMG study (placing it as fourth in the top-tier of obstacles).

Both Deloitte and KPMG have performed similar studies in the past [51,52]. The results of the KPMG study closely reflect those of Deloitte, with some minor changes in rank towards the bottom of the distribution. This is in sharp contrast to conjectures in the literature that with major discoveries and events, the importance of certain obstacles has already declined, thus indicating the dynamic nature of innovation [53]. The results of the Deloitte study reveal a wildly different set of obstacles and priorities, but this may be due to the specific characteristics of their sample which was not pan-European [52].

Moreover, the KPMG survey includes an industry breakdown informing that the top obstacle for financial services is the lack of budget; for consumers goods and products it is the lack of strategy and vision; for tech firms it is politics/turf wars/no alignment; and for pharmaceuticals it is cultural issues [16]. This information provides a very strong hint that the relative importance of obstacles may vary according to discriminants such as the industry or sector of operation.

The picture that emerges remains fuzzy, at best, and raises significant questions as to whether a consensus can be achieved regarding the obstacles to innovation. (Such a consensus could be useful for instance to drive regulatory, financial, and organizational interventions in support of innovation.) Thus, studies based on questionnaires conducted and reported by consulting companies such as Deloitte and KPMG are considered only to inform the interpretation of the formal datasets [54–56].

2.3. The research perspective

To resolve the question on the consensus about the obstacles to innovation, the findings from the practitioners are complemented by analysis of another -academic- perspective. Thus, current findings of research academic papers, ranging from narrative articles and reports to systematic reviews of the relevant literature, are addressed.

While narrative papers give a reasonable starting point, they often have a narrow focus and lack methodological transparency, making them very difficult to duplicate. More importantly, individual studies are quite fragmented and disconnected. Thus, there is a slew of second-level studies on the obstacles to innovation has emerged. The main objective of such systematic reviews and meta-studies is to address specific review questions by exploiting and synthesizing all the available research done in the area. In contrast to narrative reviews, second-level studies typically include a detailed methodology, clarify their rationale, and enumerate the assumptions applied. They reduce the fragmentation effectively by covering broad areas and providing overview and insight into the obstacles to innovation in manufacturing companies, service facilities, public sectors, etc. [54,57,58].

Starting with systematic reviews allows constructing a map of existing knowledge (including the patterns that already appeared from the business perspective). The search, selection and review process are summarized and presented in [18]. Some of the selected meta-studies can be clustered roughly across the axes of public vs. private ownership and service vs. manufacturing (Table 5).

Table 5. Dimensional clustering of the systematic reviews.

Dimension	Systematic reviews fully (or mostly) in each cluster
Public sector	Cinar et al., 2019 [54] de Vries et al., 2015 [59] Moussa et al., 2018 [60]
Private sector	Lee et al., 2019 [57] Ulvenblad et al., 2018 [58] Zanello et al., 2016 [61]
Services	Cinar et al., 2019 [54] de Vries et al., 2015 [59] Moussa et al., 2018 [60] Lorenz et al., 2012 [62] Hjalmarsson et al., 2014 [63]
Manufacturing	Ulvenblad et al., 2018 [58] Zanello et al., 2016 [61]

For example, [58,59,61–63] investigated innovation environment in either manufacturing or service-oriented firms, whereas obstacles to innovation in publicly- or privately-owned firms were widely studied by [54,57,60,61]. One possible explanation is that obstacles, as well as innovation itself, have complex, multi-level and dynamic nature [54,64]. Many researchers indicated the influence on the obstacles by different factors like policy area [54], innovativeness, size of the firm, sector affiliation [62,64], location [58,62] and country [65].

Most of the studies focus on defining obstacles across major discriminants like sector of operation or ownership [17,22,57,58,62,66–69]. On the other hand, firm size or socio-economic environment the firm operates in is receiving considerably less attention [54,57,60,61,70,71].

The review showed that although there are some common barriers inherent and significant in most companies (like organizational structure, human resources, or cost factor), when it comes to the companies in a specific type of ownership (public or private) or a specific sector of operation (manufacturing or service) the actual barriers distribution is quite divergent. For example, lack of technical and market information is considered a barrier in the service industry but is not an issue in manufacturing; in the same vein, organizational structure and culture appear to be less crucial for firms operating in the private sector compared to publicly owned companies [54,57,61].

So, careful examination of the latest systematic reviews confirms that there is no single consensus when barriers to innovation are discussed in broad terms. In fact, the relative importance of the various barriers to innovation is mitigated by a number of parameters, such as size of the firm and number of employees, whether the firm is publicly or privately owned and whether it is a manufacturing or a service-oriented enterprise. Most importantly though it appears that the socio-economic environment in which a firm operates plays a crucial role in the relative importance of the various barriers to innovation. Thus, there is no need for consensus; rather, there is a need for a closer look at the obstacles to innovation within a specific and well-defined context.

The situation is further complicated by the fact that innovation is a capacity that needs to be developed and practiced often by the firm, and thus it may tend to exhibit a definite dynamic, or temporal, nature. (Some authors do argue that, with the digital revolution, the importance of certain barriers has already declined [63].)

While this overview of the reviews helped to identify and finally define the major dimensions (firm- and operational-level variables), it also brought up an important concept of clustering the obstacles to innovation.

2.4. An emerging taxonomy of the obstacles to innovation

The diversity of the reviewed studies brings an interesting twist on the multi-dimensionality of innovation; thus, it is apparent that each meta-study presents a "unique" set of obstacles by resorting to diverse naming or titles of the obstacles culled from different sources. For example, obstacles associated with financing the innovation may be referred to as cost, budget, finance, investment, etc.

This is due to the fact that sometimes the same obstacle in intent is described with different wording: cultural issues vs. risk-averse culture or recruiting vs. lack of skills. In certain instances, one has to narrow down to the definitions provided (or not) to realize that ineffective administration (defined as "logistical problems, such as lack of training, inadequate support for end users, insufficient citizen visits, workload, high turnover, top-down managerial thinking, lack of intra-organizational coordination, ambitious or unclear goals, inadequate incentives, lack of leadership, slow decision-making and losing enthusiasm") may not exactly be the same as lack of executive support and may in effect combine a series of obstacles that other studies treat as district [54].

Even in cases where similar concepts can be harmlessly combined into underlying categories, some studies may introduce different definitions or depth of detailing. For instance, most of the studies present the lack of covering expertise or competencies as a single, unique obstacle, whereas some authors differentiate such competencies further as marketing, technical or management [60,63,72].

To avoid or at least reduce the tangle between the numerous naming and titles of the obstacles the initial map of existing knowledge and patterns generated from the overview of the reviews is augmented by the findings from the most recent research, i.e., narrative studies, on the topic. The primary focus is on exploring the historical narrative of classification or clustering of the obstacles to innovation, defining the commonly used and established variants in academic research, and setting the basis of the classification schema in the scope of this thesis.

First, the most common (and one of the earliest) grouping of the barriers to innovation is as *external* (arising when firms acquire resources or knowledge externally) and as *internal* (normally associated with difficulties in implementing internal changes in their organizational processes) to the firm. Such differentiation of obstacles by the environment was presented back in 1969 when [40] studied community- and organization-related obstacles to innovation. This classification alleviates the prioritizing and decision-making processes in the firms by identifying the factors that can be influenced within the firms and the factors that are "partially or completely beyond" their influence [64]. It was also in contrast suggested that this approach is oversimplified and does not capture the multi-actor nature of the factors and processes hampering innovation [54].

To include the actors involved in innovation processes, there is a catching suggestion to categorize the barriers to innovation depending on the outcomes or consequences they produce for the firms. Addressing this issue, in early 2012, [19] introduced the terms *revealed* and *deterring* barriers. The authors stated that innovative firms, also called innovators, the ones that were already engaged in innovative activities, tend to perceive the barriers as hampering factors that needed to be overcome, which did not really slow down or stop innovation, but facilitate learning experience ("revealed barriers"). In contrast, non-innovative firms, or non-innovators, perceive these barriers as "insurmountable" barriers prohibiting them from engaging in innovation ("deterring barriers") [19,73–75].

The different perceptions of innovative and non-innovative firms caught the attention of researchers from early the 1980s [45] and this perspective indeed adds another stroke to the analysis of innovation gap from the firms' point of view, as it helps to drive the development of new and more nuanced government policies and the implementation of targeted interventions in support of innovation (specifically for non-innovators).

At any rate, the described binary classification schemas (although important) do not significantly contribute to resolving the tangle between the numerous naming and titles of the obstacles to innovation identified earlier. Further review of the most recent research on obstacles to innovation augments the findings from meta-studies to set up the basis and historical narrative of the broader and more comprehensive classification schema.

Thus, a review of almost 100 studies in [18] helps to distinguish six major themes across which the obstacles to innovation in current research can be clustered:

- Market;
- Finance;
- Knowledge;
- Access to technology and information;
- Organizational structure and culture; and
- Economy and regulations.

This system is detailed in Table 6 along with the actual naming of the obstacles from the studies that are clustered within each theme, as well as their occurrences in the reviewed studies. While one may argue about the relative arbitrariness of this (and all other similar) schemes, the objective here is to determine whether broader trends and themes can be inferred from this elementary analysis.

The list is quite like the one identified by [39] with the addition of the issues related to organizational structure and culture, and regulations. Most importantly, the current classification schema is very fit well and works as the “noise-reduction” filter in the processing of the obstacles to obstacles to innovation presented in CIS (Table 2).

In fact, Table 7 shows how the obstacles to innovation in each CIS release are clustered across the described six main themes or clusters and reports the occurrence of each obstacle in CIS releases. Coupled with Table 2, Table 7 highlights how they evolved with time, and how the dominant list of obstacles appears to have crystallized in CIS releases in 2018 and 2020. Specifically, it can be observed that obstacles related to Technology and information, Organizational structure and culture, and Economy and regulations gradually lost their place in the list, leaving only three clusters in CIS 2012 and later.

Table 6. Identified clusters of the obstacles to innovation in research literature.

Cluster	Main obstacles	Occurrences in literature
Market	Uncertain market demand	33
	Lack of collaboration partners	27
	Dominated market by competitors/high competition	21
	No need of innovation	10
	Issues in supply chain	8
	Lack of cooperation with customers	7
	Previous innovations	6
Finance	Lack of finance/budget/funding	37
	High costs of innovation	28
	Lack of grants/subsidies/ventures and investors	16
	Lack of internal finance	15
	Uncertain returns on investments	7
Knowledge	Lack of competencies/qualified skills/employees	53
	Lack of training and incentives	9
	Lack of competencies/skills in technology	7
	Complexity of innovation	5
	Lack of competencies/skills in management	4
	Lack of competencies/skills in marketing	3
Technology and Information	Unavailable technology/weak infrastructure	28
	Lack of information on technology	22
	Lack of information on market	17
	Lack of protection mechanisms/IPRs	8
Organizational structure and culture	Poor organizational culture/rigidity	29
	Weak management and administration	16
	Lack of internal communication/strategy	15
	Risk aversion	8
	Resistance to change	4
Economy and regulations	Regulations	26
	Economic risks/uncertainty	13
	Laws	9
	Lack of government support	8
	Standards	5
	Poor state of economy	5
	Political risks/instability	4

Table 7. Identified clusters of the obstacles to innovation in CIS.

Cluster	Obstacles	Occurrences in CIS									
		1996	2000	2004	2006	2010	2012	2014	2016	2018	2020
Market	Uncertain market demand			✓	✓	✓		✓	✓	✓	✓
	Lack of collaboration partners			✓	✓	✓		✓	✓	✓	✓
	Lack of information on markets	✓	✓	✓	✓	✓					
	High competition			✓	✓	✓	✓	✓	✓	✓	✓
	Low market demand			✓	✓	✓	✓	✓	✓		
	Lack of customers responsiveness	✓	✓								
	Previous innovations			✓	✓	✓		✓	✓		
Finance	Lack of adequate finance	✓	✓			✓					
	High costs	✓	✓	✓	✓	✓	✓		✓	✓	✓
	Lack of external finance (credit or private equity)					✓		✓	✓	✓	✓
	Difficulties in obtaining public grants or subsidies							✓	✓	✓	✓
	Lack of internal finance			✓	✓	✓		✓	✓	✓	✓
Knowledge	Lack of skilled employees within enterprise	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Lack of good ideas							✓	✓		
	No compelling reason to innovate							✓			
	Lack of access to external knowledge									✓	✓
	Different priorities within the firm									✓	✓
Technology and information	Lack of information on technology	✓		✓	✓	✓					
Organizational structure and culture	Organizational rigidities	✓	✓								
Economy and regulations	Problems of regulations fulfilling	✓	✓								
	Excessive economic risks	✓	✓								

✓ *reported for non-innovators only*

In summary, the historical overview of the obstacles to innovation and their presence in the research literature and CIS releases across the years clearly demonstrated the tangle and the need for a proper adjustment of the factors under consideration, such as noise-reduction filter.

The classification or taxonomy of the obstacles developed in this chapter sufficiently resolves the tangles within the obstacles identified both in the research literature and in CIS. Moreover, the CIS methodology can be used as a relevance filter, considering the dynamic nature of the innovation barriers.

Thus, this thesis proceeds with an analysis of obstacles to innovation, following the now universally accepted taxonomy of the CIS methodology, clustered across three major thematic categories defined as *finance*, *market* and *knowledge.*

3. Data

Unraveling the mysteries behind the innovation gap, the objective of this thesis is to ground the analysis on a rich enough dataset that will provide an increased level of confidence in the outcome and can be used for further comparative or extended future research. The primary focus is on the publicly available, well-established data which excels in comprehensive sample size and coverage, rigorous methodology, and justified credibility and accuracy.

3.1. Eurostat data

A comprehensive search revealed that one of the resources of extensive data on innovation that meet the criteria is Eurostat data from its set of CIS. These surveys are designed to assess the innovativeness of different sectors and regions and executed by national statistical offices in the 27 EU member states, in the EFTA countries and in states with a candidate status for accession to the EU. The public data release normally takes place two and half years after the end of the survey reference period starting from 1992 and is managed by Eurostat – the statistical office of the EU [2], which also uses CIS for its annual European Innovation Scoreboard.

Each CIS provides analytical data broken down by countries and addresses numerous innovation composites, like drivers and barriers of innovative activities (or the lack thereof) in their firms. In the context of this thesis, CIS data are used to examine whether the relative importance of the various obstacles to innovation varies with firm size, sector and innovativeness of the firm. As a matter of choice, the presentation is based on a group of several countries with distinct socio-economic profiles and diverse institutional models of work organization.

The presentation of the publicly available data on the Eurostat platform occurs in tabular form and can be adjusted across six main parameters. Each parameter includes several options to be selected for further analysis, so an individual country, firm size class, sector or barrier can be studied independently. Table 8 summarizes the parameters and the options available for selection with their corresponding code on the example of CIS 2020 database.

Table 8. List of CIS data parameters and components in CIS 2020.

Parameters	Options
Geopolitical entity	• 22 countries (reported in CIS 2020 release)
Enterprise	• Total • Innovative enterprises • Non-innovative enterprises
Size classes	• Total • From 10 to 49 employees • From 50 to 249 employees • 250 employees or more
Statistical classification of economic activities in the European Community (NACE Rev. 2)	• Agriculture, forestry, and fishing • Innovation core activities • Industry (except construction) • Mining and quarrying • Manufacturing • Electricity, gas, steam and air conditioning supply • Water supply; sewerage; waste management activities • Construction • Services of the business economy • Wholesale/retail trade and repair of motor vehicles • Transportation and storage • Accommodation and food service activities • Information and communication • Financial and insurance activities • Real estate activities • Professional, scientific and technical activities • Administrative and support service activities
Barriers	• Lack of internal finance • Lack of external finance (credit or private equity) • High costs of innovations • Lack of qualified employees within the firm • Lack of collaboration partners • Difficulties in obtaining public grants or subsidies • Uncertain market demand for innovations • High competition in the relevant market • Lack of access to external knowledge • Different priorities within the firm
Level of importance	• High • Medium • Low • None
Time	• 2020
Time frequency	• Annual
Unit of measure	• Number • Percentage

In the scope of this thesis for the sake of methodology consistency the data in each release is extracted:

- in numerical form (and not the Percentage option);
- for innovative and non-innovative firms (and not the Total option);
- for three size classes (and not the Total option);
- for seven economic activities (and not the activities with no data reported for the obstacles);
- for all reported obstacles to innovation;
- with two levels of importance (focusing only on firmly expressed opinions); and
- for all selected countries.

Regarding the levels of importance, for CIS the firms were asked to rate their perceived degree of importance of each of the factors in Table 8 hampering their innovation activity (or lack thereof). They were provided a 4-point Likert scale, with the degree of importance ranging from “Not Important” and “Low” to “Medium” and “Highly Important”. The advantage of a 4-point Likert scale is that it does not force the participant to take a stand on a particular topic but allows a degree of agreement that can accommodate neutral or undecided feelings.

Interestingly, the reporting of the results until CIS 2018 occurred in a binary fashion, recording the number of firms that have a very definite position on each obstacle: either that it is “Highly Important” or “Not Relevant” at all [14,76]. Removing opinions that were relatively uncertain or neutral towards a specific obstacle (“Low” and “Medium” importance) was a Eurostat choice to reduce noise in the data [21]. So, the combination of a 4-point Likert scale followed by an emphasis on the two extremes of the scale places the focus squarely on the respondents that appear to have a clear and informed opinion [67]. And although the neutral and relatively uncertain opinions became publicly available recently, this thesis proceeds with an analysis of the definite opinions on each obstacle.

An important caveat of the recorded data is that they reflect the respondent’s perceptions regarding the barriers hampering innovation activity. As in all such surveys on innovation, it is expected that there is a correlation between the perception of the importance of an obstacle and its actual impact on the innovativeness of the firm, regardless of whether these are revealed or deterring barriers [77].

Thereby, Table 9 illustrates how the raw CIS data extracted in the described way is reported on the example of a small excerpt for one obstacle (“Lack of internal finance”) from CIS 2016 collected from the innovative firms in Germany. Table 9 shows the number of firms that expressed a definite opinion on the importance of the obstacle (either highly important or not important) with responses differentiated across three size classes and seven economic activities.

Table 9. Excerpt of the raw CIS data: Innovative firms in Germany in CIS 2016.

Size class	**From 10 to 49 employees**		**From 50 to 249 employees**		**250 employees or more**	
Level of importance	**High**	**None**	**High**	**None**	**High**	**None**
Economic activities:						
Mining and quarrying	30	90	1	51	1	14
Manufacturing	4,107	10,593	1,111	4,744	243	1,545
Electricity, gas, steam, and A/C supply	56	161	24	166	13	41
Water supply, sewerage, waste disposal	202	640	19	220	1	38
Transportation and storage	846	2,461	358	1,210	25	186
Information and communication	1,755	2,935	208	1,100	60	201
Financial and insurance activities	167	452	13	593	28	439

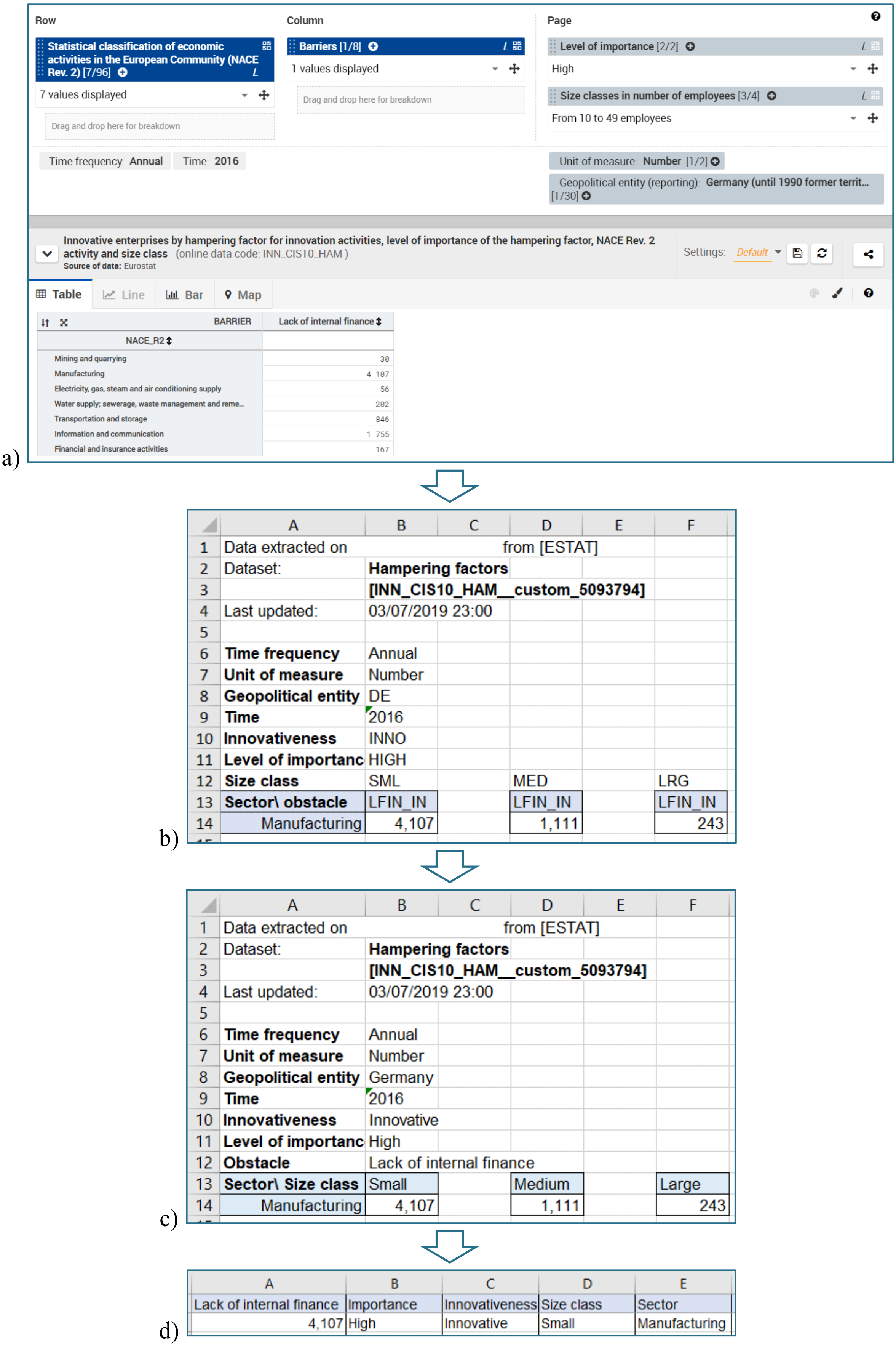
Raw data obtained in this way is not directly conducive to analysis and various attempts have been made in the past to tabulate them in a form that can be amenable to statistical analysis [14]. To facilitate the analyses in this thesis, a novel way of agglomerating the raw data is presented in the form of a set of systematic steps that guarantee the reproducibility of the results. These steps are illustrated here for the running example of CIS 2016 data for German innovative firms and the obstacle “Lack of internal finance”.

Step 1 – Customization of the CIS data by focusing on the innovation “hampering factors” and querying the CIS database available online for the parameters and options of Table 8 (Figure 3 (a)).

Step 2 – Extraction and downloading of the relevant data in a custom .xlsx format that is amenable to pre-processing (Figure 3 (b)).

Step 3 – Transformation of the data in the custom data sheet in a way that agglomerates them in relevant bins of size and sector for each obstacle (Figure 3 (c)).

Step 4 – Articulation of a local database with arrays of data in the form (obstacle, importance, innovativeness, size class and sector) on which advanced statistical tools can now be applied (Figure 3 (d)).



b)

	A	B	C	D	E	F
1	Data extracted on			from [ESTAT]		
2	Dataset:	**Hampering factors**				
3		**[INN_CIS10_HAM__custom_5093794]**				
4	Last updated:	03/07/2019 23:00				
5						
6	**Time frequency**	Annual				
7	**Unit of measure**	Number				
8	**Geopolitical entity**	DE				
9	**Time**	2016				
10	**Innovativeness**	INNO				
11	**Level of importanc**	HIGH				
12	**Size class**	SML		MED		LRG
13	**Sector\ obstacle**	LFIN_IN		LFIN_IN		LFIN_IN
14	Manufacturing	4,107		1,111		243

c)

	A	B	C	D	E	F
1	Data extracted on			from [ESTAT]		
2	Dataset:	**Hampering factors**				
3		**[INN_CIS10_HAM__custom_5093794]**				
4	Last updated:	03/07/2019 23:00				
5						
6	**Time frequency**	Annual				
7	**Unit of measure**	Number				
8	**Geopolitical entity**	Germany				
9	**Time**	2016				
10	**Innovativeness**	Innovative				
11	**Level of importanc**	High				
12	**Obstacle**	Lack of internal finance				
13	**Sector\ Size class**	Small		Medium		Large
14	Manufacturing	4,107		1,111		243

d)

A	B	C	D	E
Lack of internal finance	Importance	Innovativeness	Size class	Sector
4,107	High	Innovative	Small	Manufacturing

Figure 3. Methodological rules for CIS data transformation.

For the example excerpted in Table 9, Figure 3 illustrates the fact that 4,107 small innovative manufacturing firms in Germany declared the "Lack of internal finance" as an obstacle of high importance to innovation. This number should be compared and contrasted with the 10,593 small innovative manufacturing firms in Germany that declared the "Lack of internal finance" as an obstacle of no importance at all to innovation (Table 9).

By focusing only on definite opinions ("votes"), that is whether an obstacle to innovation is perceived as highly important or not important at all by a firm, the respective variable is converted to a binary one ("High" vs "None"). This new, carefully calibrated format with the binary votes allows for the use of sophisticated statistical analysis algorithms.

Clearly, the series of steps articulated above can be applied to other obstacles to innovation, to other variables surveyed in the CIS but also to other data sources (as will be demonstrated in Chapter 7 for intellectual property outputs).

3.2. WIPO data

To reinforce the analysis of the innovation gap as measured by the innovation obstacles perceived by EU firms the thesis also utilizes the extensive data on innovation provided by WIPO, the United Nations agency "created to promote and protect intellectual property across the world".

Specifically, the WIPO data helps to augment the thesis with rich and comprehensive data to examine additional qualifiers of the innovation process such as the concept of clustering, and the issue of gender and diversity.

The annual GII reports released by WIPO in consortium with Cornell University and INSEAD Business School were already introduced in Chapter 1. Primarily presented as the ranking of the countries based on their innovation performance (capacity and success in innovation), these reports "track the most recent global innovation trends" and strive "to capture as complete a picture of innovation as possible".

While GII reports provide reliable (and regular) data on innovation, each one of them offers additional insights on the relevant innovation subjects in the form of special sections. One of the remarkable examples is a working paper identifying the world's top-100 innovation clusters based on their patent activity [37]. This is a novel attempt to identify global innovation hotspots through patent filings on a global scale and to compare cluster performance within and across countries in a systematic, data-driven way.

WIPO report [37] addressed approximately 950,000 patent applications published under the Patent Cooperation Treaty (PCT) system between 2011 and 2015. The PCT system is operated by WIPO and has 142 member countries that together account for more than 98 percent of patent filings worldwide.

Their reliance on PCT filing data was motivated by two reasons. First, PCT enforces the same strict application rules around the world and collects information based on uniform filing standards. It is thus expected that the data collected will be comparable in nature and of high quality. Second, seeking an international PCT patent is a costly and lengthy process that will only be pursued by applicants with a reasonable expectation of sufficiently high return. Thus, PCT data are more likely to capture the most commercially valuable inventions. On the downside, not all international patent applications go through the PCT system, and not every PCT application will eventually result in a granted patent.

The special section of WIPO GII report of 2017 proceeded further including the data on gender representativeness of women inventors among all inventors located in a particular hotspot [78]. (Subsequent editions of the annual WIPO report omit this very important information.)

Thus, WIPO data typically included the data on the:

- Cluster localization;
- Country;
- Total number of PCT filings from a cluster;
- Number of patent filings of the most innovative firm in the cluster (as measured by its patent applications);
- Industry sector that the largest number of cluster patents filed belong to;
- Number of patent filings in the industry sector with the largest number of cluster patents filed;
- Number of patent filings in the cluster contributed by public research organizations (PROs);
- Average share of women inventors; and
- Total population of the geographical area.

As it can be observed, among the top 10 clusters based on the PCT filings [37] Japan and USA report the leading positions with each country reporting three top clusters. They are followed by two clusters from China and the remaining two clusters are located in Korea and France (Table 10). The full list of top-100 clusters from WIPO report is presented in Table C6 in Appendix C.

Table 10. Cluster ranking based on total 2011-2015 PCT filings*.

#	Cluster localization	Country	Total filings	Top entity filings	Top sector	Top sector filings	Total PROs** filings
1	Tokyo–Yokohama	JP	94,079	6,021	Electrical engineering	5,927	2,728
2	Shenzhen–Hong Kong	CN	41,218	13,355	Electrical engineering	16,982	495
3	San Jose–San Francisco	US	34,324	2,231	Electrical engineering	6,281	1,167
4	Seoul	KR	34,187	5,675	Electrical engineering	3,555	3,692
5	Osaka–Kobe–Kyoto	JP	23,512	2,445	Electrical engineering	1,951	988
6	San Diego	US	16,908	9,485	Electrical engineering	3,990	524
7	Beijing	CN	15,185	2,141	Electrical engineering	3,432	2,885
8	Boston–Cambridge	US	13,819	843	Chemistry	1,714	2,294
9	Nagoya	JP	13,515	5,730	Mechanical engineering	1,757	257
10	Paris	FR	13,461	1,036	Mechanical engineering	1,090	1,292

* *adapted from* [37]; ** *Public Research Organizations*

Interestingly, a similar pattern was observed later in 2017 [78] with USA reporting 31 innovation clusters, followed by Japan, China, France and Korea (with the intervention of Germany into the list) (Table 11).

Table 11 is another illustration of the global innovation gap. Indeed, even at the cluster level, innovation activity is mostly concentrated in a handful of leading countries that possess the human and financial capital to create new knowledge and the market acumen to capitalize on it.

Table 11. Top clusters worldwide in 2017*.

Country	Number of clusters	Total filings	Average share of women inventors (%)
United States	31	157,068	14.7
Germany	12	52,261	9.2
Japan	8	139,804	7.9
China	7	67,911	29.1
France	5	19,525	18.4
Republic of Korea	4	42,249	26.5
Canada	4	7,140	14.6
United Kingdom	3	9,666	15.9
India	3	4,497	14.7
Switzerland	3	7,999	14.6

* *adapted from* [78]

While one of the benefits of CIS data is their repeatability and broad methodological consistency, WIPO reports on the clusters provide standalone, independent datasets. For instance, [37] report already combines the clusters' PCT filings from several years and an attempt to introduce more recent studies leads to major overlaps. (For example, the later reports, covering the 2012-2016 and 2013-2017 time spans, clearly overlap.) A special report from [78] was a one-year release and has not been yet reproduced on more recent data.

With this caveat and considering their elementary format, the raw WIPO data do not necessitate any significant preprocessing.

4. Methodology

Many researchers and analysts aiming to examine and measure such a composite phenomenon as innovation resort to a great variety of instruments and tools. The list of the methods and approaches identified in the literature varies from descriptive statistical analysis to various modelling techniques and multi-criteria decision analysis (MCDA) tools.

4.1. Probit regression

One of the most common practices in innovation research though is to employ regression analysis. Considering that the CIS data format leads in effect to categorical, and often binary, variables it should be appreciated that in such cases regression models produce nonlinearities in the predicted probability metrics.

Most regression models for categorical dependent variables produce nonlinearities in the predicted probability metric necessitating the use of NLPM for the analysis. NLPM are regression models that employ a nonlinear transformation to obtain a model that is linear in its parameters. One of the best known NLPM for the analysis of ordered, categorical, nonquantitative choices, outcomes and responses is the Probit model, which models the probability of a dichotomous or binary outcome as a linear combination of categorical predictors [21,22].

Thus, in the scope of the study aimed to identify what impedes innovation the objective of the analysis is to estimate the probability $P(i)$ of the event that "firms in a specific class (firm size and sector) assess a given obstacle i as highly important or not". The underlying assumption is that the binary variable $P(i)$ (with values of 1 or 0), is in fact a partially observed continuous latent variable *or,* at least, a set of discrete outcomes of a continuous variable that can be ordered by some criterion [79].

A generic formulation of the model with a binary dependent variable (adapted from [79]) assumes that an unobserved (or latent) variable Y_i^* is generated by a classical linear regression model of the form:

$$Y_i^* = x_i^T \beta + u_i = \beta_0 + \beta_1 x_{i1} + \beta_1 x_{i1} + \cdots + \beta_n x_{in} + u_i \tag{1}$$

where:

Y_i^* is a continuous index variable for observation i that is latent, or unobservable;

x_i^T is a 1xN row vector of regressor values for observation i;

β is a Nx1 column vector of regression coefficients;

$x_i^T\beta$ ix a 1x1 scalar for index function for observation i; and

u_i is a random error term for observation i.

Next, the indicator variable Y_i represents the observable binary outcomes, which is related to the unobserved dependent variable Y_i^* as in:

$$Y_i = 1 \; if \; Y_i^* > 0 \tag{2.1}$$

$$Y_i = 0 \; if \; Y_i^* \leq 0 \tag{2.2}$$

Specifically, Y_i represents the probabilities below as observed realizations of a binomial process:

$$\Pr(Y_i = 1) = \Pr(Y_i^* > 0) = \Pr(x_i^T\beta + u_i > 0) \tag{3.1}$$

$$\Pr(Y_i = 0) = \Pr(Y_i^* \leq 0) = \Pr\,(x_i^T\beta + u_i \leq 0) \tag{3.2}$$

Next, Probit model uses $\Phi(Z)$ (cumulative distribution function of the standard normal distribution) to analytically represent the binomial probabilities (3.1) and (3.1):

$$\Pr(Y_i = 1) = \Pr(Y_i^* > 0) = \; \Phi(x_i^T\beta) \tag{4.1}$$

$$\Pr(Y_i = 1) = \Pr(Y_i^* \leq 0) = \; 1 - \Phi(x_i^T\beta) \tag{4.2}$$

For the case at hand, Probit regression is based on the assumption that the probability $P(i)$ that obstacle i is highly important for a given firm can be computed as:

$$P(i) = \beta_{i0} + \beta_{i1}x_1 + \beta_{i2}x_2 + u_i \tag{5}$$

where the independent or regressor variables of size and sector are categorical and binary; the regression coefficients β_{i0}, β_{i1}, and β_{i2}, need to be computed; and u_i is a normally distributed random error term for each observation i [79,80].

The full list of the *independent* variables (regressors) is summarized in Table 12 with the corresponding notes and coded levels developed from the processed and calibrated CIS data. It should be noted that the thesis proceeds with its own nomenclature for the variables, as SML, MED and LRG indicate the firms in the small, medium and large size classes, and PROD(uction) and SERV(ices) indicate sectors of operation.

Often the effect of one independent variable is contingent upon the level of another independent variable. For instance, it is natural to expect that large firms are more prone to innovation than small ones. When interaction effects are suspected to exist, the Probit model needs to be adjusted accordingly [81]:

$$P(i) = \beta_{i0} + \beta_{i1}x_1 + \beta_{i2}x_2 + \beta_{i12}x_1x_2 + u_i \tag{6}$$

where the coefficient β_{i12} needs to be computed as well.

Table 12. Independent variables.

Variables	Notes	Level
Size class:		
SML	10 to 49 employees	1
MED	50 to 249 employees	2
LRG	More than 250 employees	3
Sector:		
PROD	Production	1
SERV	Services	2

It should be noted though that it is not possible to determine the nature of an interaction effect for NLPM based on the β_{i12} coefficient alone, be that through its sign, magnitude, or statistical significance [80]. In fact, the coefficient of the interaction term should not be used at all to draw conclusions in categorical models such as Probit [82]. Purely for exploratory purposes the use of the interaction term is presented in Appendix A (Table A4). The effect of the interaction term β_{i12} in (6) though is felt through the adjustment it imposes on the values of the coefficients β_{i0}, β_{i1}, and β_{i2} compared to those in the non-interactive model in (5).

4.2. Marginal effects

In any case, the estimated regressions coefficients of Probit models are not particularly useful from a practical standpoint. While the sign and statistical significance of β_{i0}, β_{i1}, and β_{i2} may be indicative of the underlying relationship, their absolute magnitude is difficult to interpret in substantive terms [81].

Assuming the zero conditional mean error equation (1) means that:

$$\mathrm{E}(Y_i^*|x_i^T) = \mathrm{E}(x_i^T\beta|x_i^T) + \mathrm{E}(u_i|x_i^T) = x_i^T\beta \text{ since } \mathrm{E}(u_i|x_i^T) = 0 \tag{7}$$

Thus, the index function $x_i^T\beta$ (also called regression function) is the conditional mean value of the latent random variable Y_i^* for given values of the regressors.

In cases when all explanatory variables are continuous and enter the $x_i^T\beta$ linearly, the partial derivatives of (7) with respect to the individual regressors are the slope coefficients β_j ($j = 1, \dots, n$):

$$\mathrm{E}\frac{\partial \mathrm{E}(Y_i^*|x_i^T)}{\partial X_{ij}} = \frac{\partial x_i^T\beta}{\partial X_{ij}} = \frac{\partial(\beta_0 + \beta_1 X_{i1} + \cdots + \beta_j x_{ij} + \cdots + \beta_n x_{in})}{\partial X_{ij}} = \beta_j \tag{8}$$

But in cases when some of the explanatory variables are binary or enter $x_i^T \beta$ nonlinearly, the partial derivatives of (7) are not so simply interpreted.

Thus, instead of stopping with the developing predictive models, Probit models are used to report an alternative metric -called *marginal effects*, or adjusted predictions- to understand how the value of an independent variable in Probit changes with a unit change in one of the regressor variables. This choice facilitates interpretation and is uniformly used in the analysis throughout this thesis. In the literature, six main approaches are presented [83]:

- MEMs (Marginal effects at the means);
- MERs (Marginal effects at representative values);
- AMEs (Average marginal effects);
- APMs (Adjusted predictions at the means);
- APRs (Adjusted predictions at representative values); and
- AAPs (Average adjusted predictions).

Marginal effects reflect how the value of dependent variable changes with a unit change in one of the regressor variables. Thus, in the scope of this study it would provide the difference in predicted importance of an obstacle between the firms in different two size classes or two sectors of operation. Meanwhile, to compute the adjusted predictions the values for each of the independent variables in the model are specified, and then the probability of the event occurring for an individual who has those values is computed. Thus, the predicted importance of an obstacle for a specific category of the firms (specified size class and sector of operation) can be obtained, which better answers the objective of this thesis.

In a multivariate model, when several regressors are included in the model, both marginal effects and adjusted predictions provide the predicted probability of the outcome for a unit change in one of the regressors while holding all other independent variables in the model constant at their mean (approaches 1 and 4) or at other representative value (approaches 2 and 5) [79,83].

In the scope of this study holding the regressor at the mean values may result in a situation where size of the firm or its sector affiliation would be determined by a fractional number, which is irrational. On the other hand, holding the regressor values at manually selected representative values deprives the accuracy and representativeness of the results.

Thus, the analysis in this thesis thus proceeds based on the Probit model in (6) and the report of the *average adjusted predictions*, to estimate the probability $P(i)$ of the event "firms in a specific class assess a given obstacle i as highly important or not".

4.3. The variables

The full list of the obstacles (i taking values from 1 to 10), thus, *dependent* variables in this study are summarized in Table 13. Following the adopted classification taxonomy, the extracted innovation barriers are "clustered" into three major groups: Finance, Market and Knowledge [77,84]. The right part of the table highlights the limitations of the CIS data, such as not all ten obstacles (crystallized by CIS 2018) appeared earlier.

As the actual list of the obstacles evolved over the years from one release to another (Table 2 and Table 7), the factors of "high cost of innovations" and "high competition in the relevant market" were absent in CIS 2014 release but returned in CIS 2016, while the factors of "lack of access to external knowledge" and "different priorities within the firm" were introduced for the first time in CIS 2018.

Table 13. Dependent variables.

Code	Definition	Cluster	CIS 2014	CIS 2016	CIS 2018	CIS 2020
LFIN_IN	Lack of internal finance	*Finance*	✓	✓	✓	✓
LFIN_EXT	Lack of external finance (credit or private equity)		✓	✓	✓	✓
H_COST	High costs of innovations			✓	✓	✓
L_SUBS	Difficulties in obtaining public grants or subsidies	*Market*	✓	✓	✓	✓
U_DMND	Uncertain market demand for innovations		✓	✓	✓	✓
H_COMP	High competition in the relevant market			✓	✓	✓
L_EMPL	Lack of qualified employees within the firm	*Knowledge*	✓	✓	✓	✓
L_PRTN	Lack of collaboration partners		✓	✓	✓	✓
L_EXTKN	Lack of access to external knowledge				✓	✓
D_PRIOR	Different priorities within the firm				✓	✓

Several parameters of the study (such as innovativeness level) were selected as control variables, that is, Probit regression is performed separately for INNO and NON-INNO firms so as not to mix perceptions of revealed and deterring barriers [77]. Similarly, the data from different countries and different CIS releases constitute separate independent samples. Thereby, the *control* variables are summarized in Table 14.

Table 14. Control variables.

Variables	Notes
Innovativeness:	
NON-INNO	Not engaged in innovation
INNO	Engaged in innovation
Year:	
CIS2014	Survey conducted in 2012-2014
CIS2016	Survey conducted in 2014-2016
CIS2018	Survey conducted in 2016-2018
CIS2020	Survey conducted in 2018-2020
Country:	
DE	Germany
PL	Poland
PT	Portugal
MK	North Macedonia
IT	Italy
FI	Finland
EE	Estonia
RO	Romania

The countries were selected based on their representativeness of the sample. Thus, the countries with the richest and most extensive coverage of the firms' categories above and the fullest availability of data were selected to present different socio-economic, cultural and innovativeness levels. In Appendix B

Validating the benchmarking example, the descriptive statistics for each country are presented in summary form. (Percentages in the tables may not add up to 100 due to rounding.) The statistics include the number of the firms and ratio of the innovators across each of the variables.

The Probit model in (6) was implemented with the STATA v17 statistical software [85]. The analysis was performed with the statistical significance set at a two-sided p-value of ≤ 0.05 [86]. The results typically include the coefficients of predictive margins (and their statistical significance) in tabular form.

For interpretive purposes, the results are then represented in graphical form. For example, Figure 4 illustrates the predictive margins, as well as their statistical significance (significant at 1%) in square brackets, for the barrier "Lack of internal finance" across the three class sizes and two sectors of operation. The computations were based on the excerpted data in Table 9.

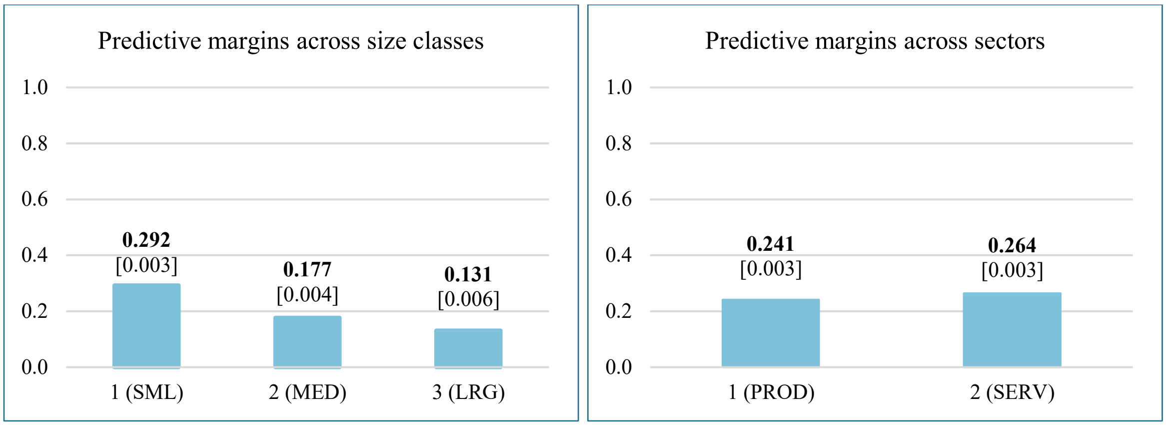


Figure 4. Predictive margins: Innovative firms assessing each obstacle as highly important across size classes and sectors in Germany in CIS 2016.

The interpretation of the results in Figure 4 is as follows. The predicted probability that a small-size firm will name "Lack of internal finance" as a highly important obstacle to innovation is about 29%. The same predicted probability for medium- and large-sized firms is approximately 18% and 13% respectively. Thus, the results broadly indicate that this barrier is slightly more important for small firms when compared to medium and large firms and has almost the same importance for firms operating in production and service industries (24% and 26% respectively).

The full ranges of predictive margins for all other obstacles and situations (as well as results for additional analysis across selected countries and CIS releases) are detailed in Appendix A (Table A3).

5. Firm layer

Based on the defined dependent variables, pre-processing of the data and regression methodology, the study proceeds to the *firm layer* aiming to deconstruct the multiple dimensions of innovation and addressing the queries related to the key characteristics of the profile of an organization that impact its innovativeness.

In Chapter 2 the main firm-level characteristics, or variables, that influence the relative importance of the obstacles to innovation in the respective firms. Thus, firms of different sizes (for instance with different numbers of employees) or firms engaged in different economic activities (for instance operating in manufacturing or service sectors) experience different issues and barriers and consequently report different perceptions and assessments.

An additional facet of such differences in perceptions in the firms is based on their "innovativeness". Such as innovators that are already engaged in innovative activities tend to perceive the barriers as hampering factors needed to be overcome. These "revealed" barriers do not really slow down or stop innovation but facilitate the learning experience. Whereas non-innovative firms perceive the "deterring" barriers as "insurmountable", prohibiting them from engaging in innovation [19,87].

5.1. Germany analysis and results

The thesis proceeds further with an analysis of the obstacles to innovation as perceived by both innovative and non-innovative firms from Germany surveyed in CIS depending on their size and sector of operation. Due to the data availability (data for Germany not released in CIS 2018 and later) the focus is on the sample of Germany from CIS 2016.

The impressive collection of responses from 106,184 firms indicates that every one out of every four firms was surveyed in 2016 in Germany (the total population in 2016 was 416,536 firms [88]). The distribution of the CIS respondents across the size classes is slightly skewed away from SML firms and increasingly towards MED and LRG firms (having 71% of the CIS sample as SML firms, 23% as MED and 6% as LRG against 84% as SML, 14% as MED and 3% as LRG in the entire population). Across the sectors of operation, 65% of the CIS sample are categorized as firms engaged in PROD and 35% as SERV activities.

Table 15 presents the descriptive statistics of the Germany sample from CIS 2016. Thus, out of 106,184 surveyed firms, 66% had introduced an innovation or had ongoing or abandoned innovation activities during the three years preceding the survey period. The 69,973 firms thus classified as INNO are distributed across size classes in a manner very similar to that of the 106,184 firms of the entire sample. It should be observed however that within classes there are significant disparities behind the overall 66% of INNO firms in the sample. For instance, within the size class, only 60% of the SML firms in the sample are classified as INNO, compared to an impressive 79% and 91% of innovators among MED and LRG firms respectively. More detailed descriptive statistics on Germany data (including the other CIS releases) are presented in Appendix A (Table A1).

Table 15. Descriptive statistics of the Germany sample from CIS 2016.

DE 2016	Surveyed firms	Percent of total firms	Surveyed INNO firms	Percent of total INNO firms	Percent of INNO firms in a category
Size class:					
SML	75,855	71%	45,387	65%	60%
MED	24,304	23%	19,083	27%	79%
LRG	6,025	6%	5,503	8%	91%
Total Size class	**106,184**	**100%**	**69,973**	**100%**	**66%**
Sector:					
PROD	68,619	65%	47,278	68%	69%
SERV	37,565	35%	22,695	32%	60%
Total Sector	**106,184**	**100%**	**69,973**	**100%**	**66%**

So, the firms were asked to rate their perceived degree of importance of a list of the factors hampering their innovation activity (or lack thereof) on a 4-point Likert scale. The focus on the definite opinions on each obstacle (either "Highly Important" or "Not Important") and within the sample of innovative firms in Germany only 37,148 (or 53%) of 69,973 firms had a very clear opinion about the significance of the lack of internal finance (LFIN_IN) for them, while the rest had ambivalent or neutral opinions about it. Across both INNO and NON-INNO firms, the definite opinion was reported from 46,434 (or 43%) of the 106,184 firms. (This is actually true for all eight obstacles, with the percentage of firms with definite opinions ranging between 38%-51% with a mean of 42%.) More details on the number of the firms expressing a clear opinion on the obstacles to innovation are presented in Appendix A

Benchmarking example of Germany (Table A2).

The data of Germany are analyzed for the 8 obstacles of the CIS 2016 edition, with the regressors being the independent variables of firm size class (small, medium, or large), sector of operation (production or services) and innovativeness (engaged or not in innovation). The econometric model was implemented with the STATA v17 statistical software, the predictive margins computed reflect the average adjusted predictions, and the analysis was performed with the statistical significance set at a two-sided p-value of ≤ 0.05. The results in tabular form for all eight obstacles are presented in Appendix A, with Table A3 detailing the coefficients and their statistical significance as well as errors and confidence intervals.

Figure 5, adapted from [28] indicates the predictive margins for each of the eight obstacles across the three class sizes for innovative and non-innovative companies separately. The Total curve demonstrates how the perceptions of the whole sample trend versus those of innovators and non-innovators.

The main observation is that INNO and NON-INNO firms do attach different importance to innovation barriers, specifically all eight obstacles are more important for non-innovative firms than for innovative ones. Introducing the firm size into analysis shows that the most significant differences in perceptions are among large-sized INNO and NON-INNO firms, especially about the financial barriers (LFIN_IN, LFIN_EXT, H_COST).

The two market barriers in the form of lack of subsidies (L_SUBS) and uncertain market demand (U_DMND) appear to be of the same importance across all the firms regardless of the size or innovativeness. The exception is the high market competition, which shows the unique pattern across all eight obstacles. Thus, while among innovators the predicted importance of H_COMP gradually falls with an increase of the firm size, among the non-innovators H_COMP appears to be much more important for large firms.

While knowledge barriers do not demonstrate an outstanding pattern, it can be observed that firms of different size and innovativeness level indeed report different importance of the innovation barriers. The focus on the firm-level characteristics helps to address the factors that inhibit innovation from the point of view of individual firms. While the first part of this analysis explores the relationship between the firm size and innovativeness, this chapter proceeds with an analysis of the importance of the innovation barriers in the firms across the sectors of operation.

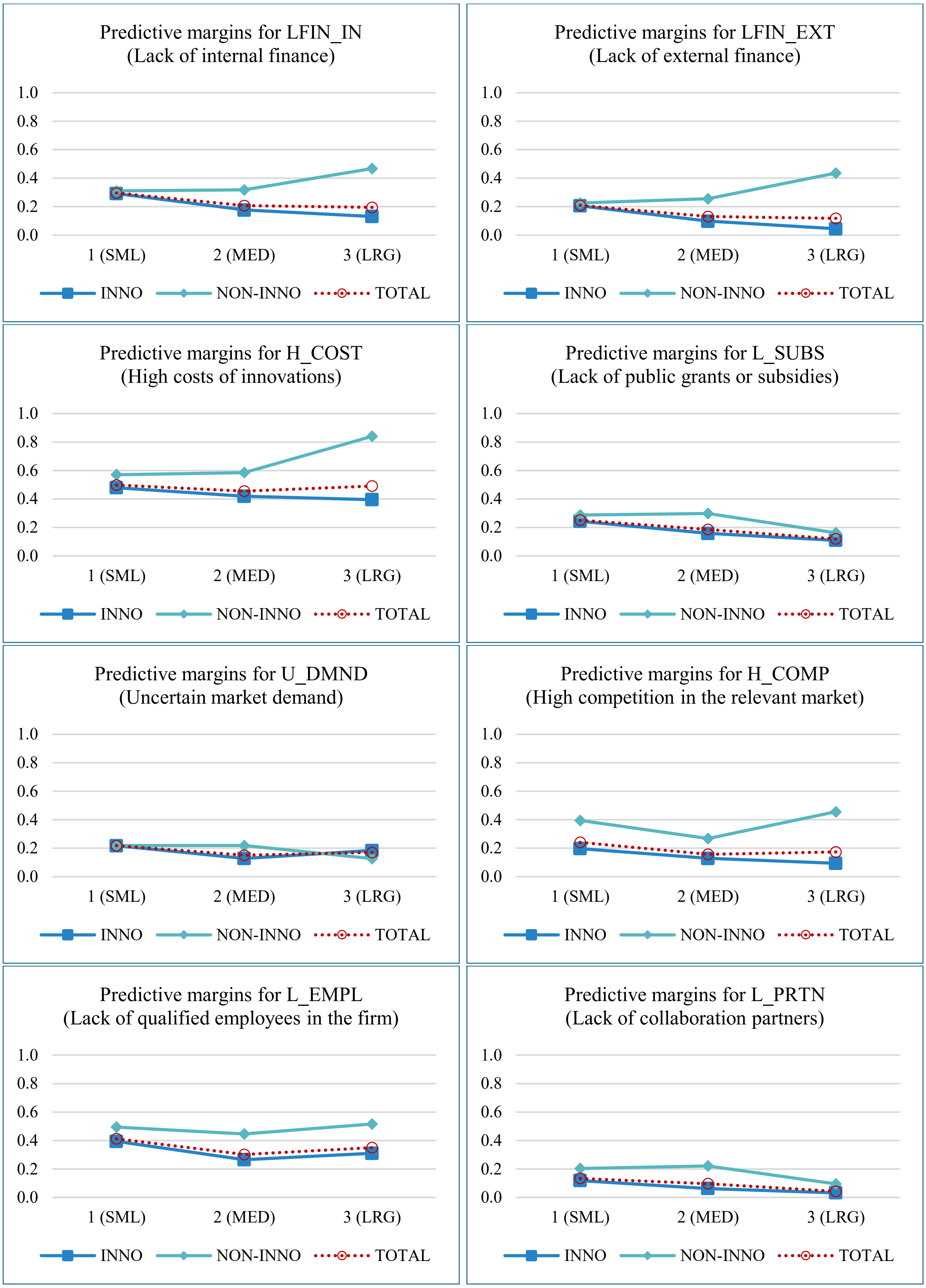


Figure 5. Predictive margins: Firms assessing each obstacle as highly important across size classes and innovativeness.

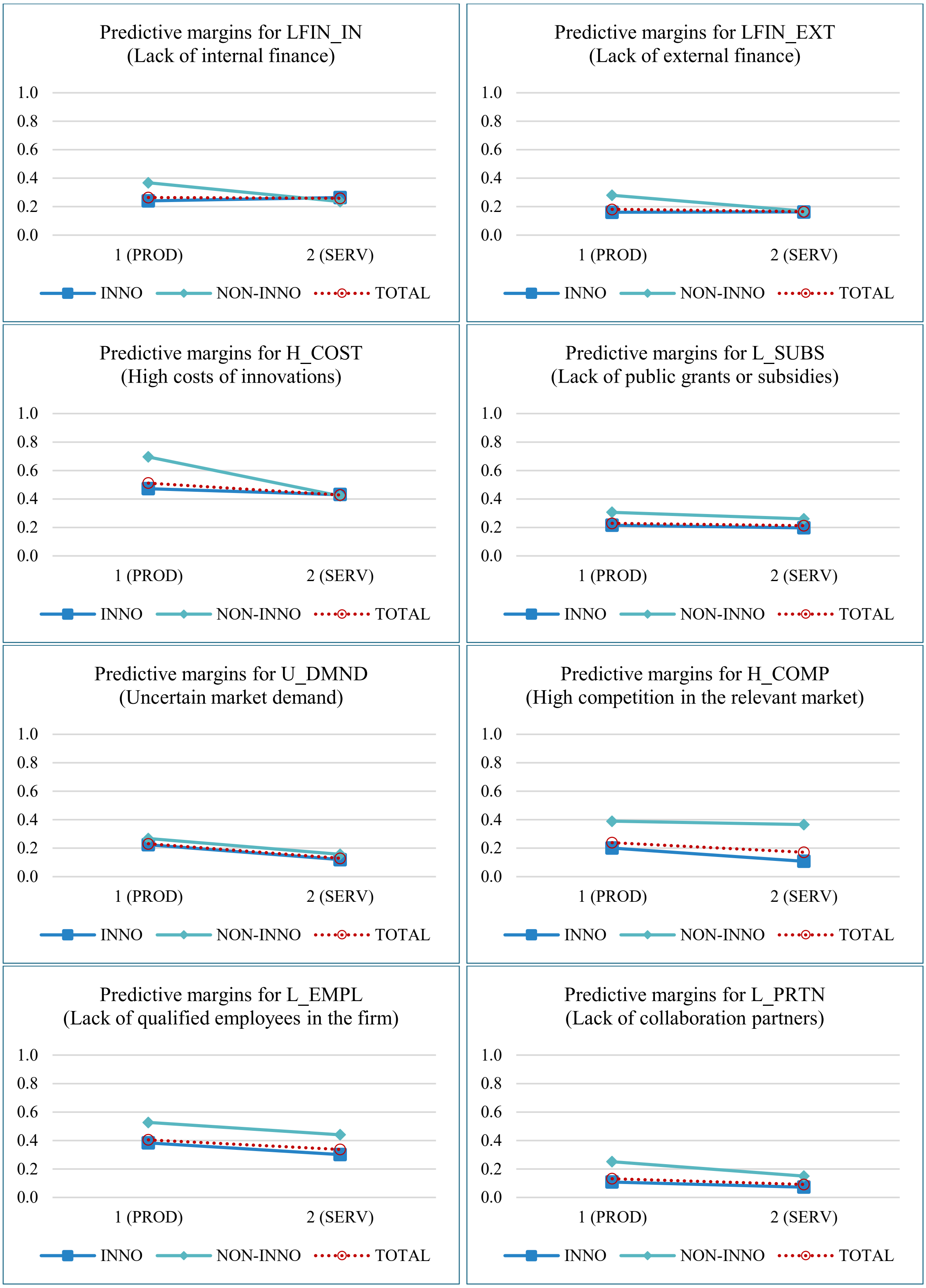


Figure 6. Predictive margins: Firms assessing each obstacle as highly important across sectors and innovativeness.

Similarly, Figure 6 adapted from [28], shows the predictive margins (and their statistical significance) across the two sectors of operation from innovative and non-innovative companies separately with the Total curve reflecting the opinions of the whole sample.

In contrast to the first variable, the differentiation of the firms' perceptions across their sector does not reveal a significant impact on the resultant predicted importance of the innovation barriers. (Non-innovators though report a slightly higher importance in almost every category.)

Another important observation is that the importance of almost every obstacle is slightly higher for the firms engaged in PROD(uction) activities compared to the SERV(ice) ones. The difference is most prominent for financial barriers.

In summary, the results thus far in this chapter demonstrate that the relative importance of the barriers to innovation varies across the firm-level characteristics such as the size and sector of operation. Moreover, such importance is significantly moderated by whether a firm has been involved or not in innovation activities [28].

5.2. Beyond the benchmarking example

While the results above reflect only the situation in Germany, a similar analysis at the firm layer was conducted for the firms operating in a host of countries with different socio-economic, cultural and innovativeness levels. The detailed presentation of the predictive margins (and their statistical significance) across the same firm-level characteristics for Italy, Poland, Portugal, Finland, Estonia, Romania, and North Macedonia are presented in Appendix B

Validating the benchmarking example.

An overview of the predicted importance of the innovation barriers in diverse countries does confirm the main trends identified for Germany. For instance, focusing on the lack of internal finance hampering innovation in these countries (Figure 7) it can be observed that the Germany pattern (importance of the obstacle decreasing with the increase in size of the firm) is also revealed (to more or less extent) in most of the described countries. One can only emphasize the Italy, Finland, and Estonia cases, where MED and LRG firms report almost the same importance of this financial barrier (in fact, almost the same importance across all three size classes in Finland).

Interestingly, the agglomeration of Finance barriers (LFIN_IN, LFIN_EXT and H_COST) in Figure 8 shows very similar patterns for all these countries. (Clustering the barriers along the main themes of Finance, Market and Knowledge allows for methodological consistency and can cover some of the gaps in the original data across countries and years.) It should be noted that the clustered Market and Knowledge themes, presented in Figure B1 and Figure B2 in Appendix B, demonstrate a similar picture as well.

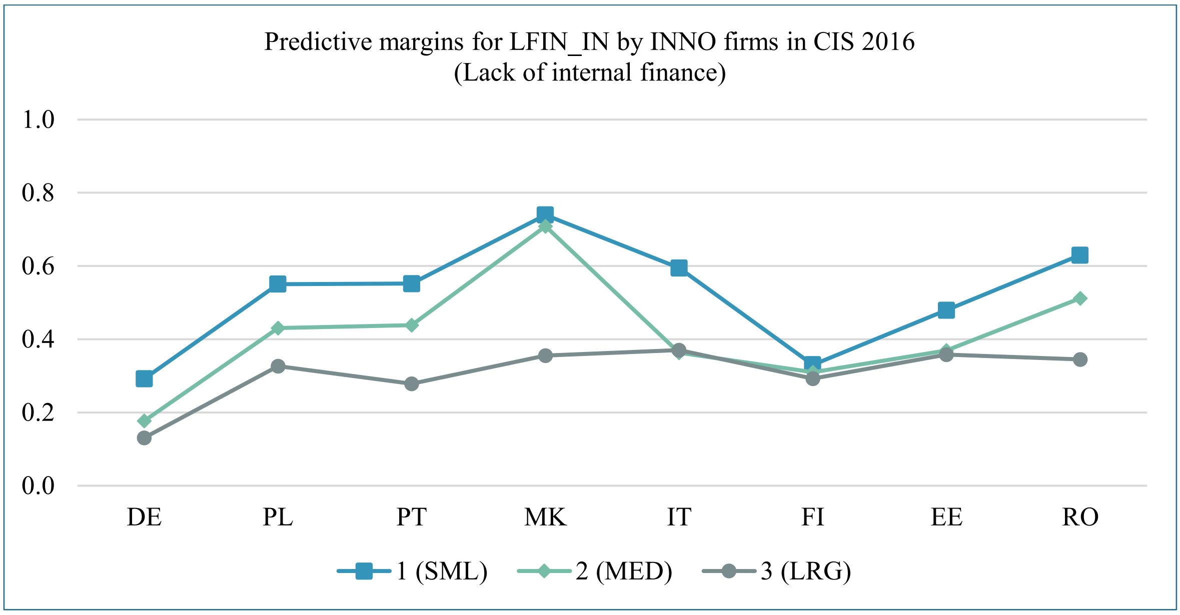


Figure 7. Predictive margins: Innovative firms assessing lack of internal finance as highly important across size classes in different countries.

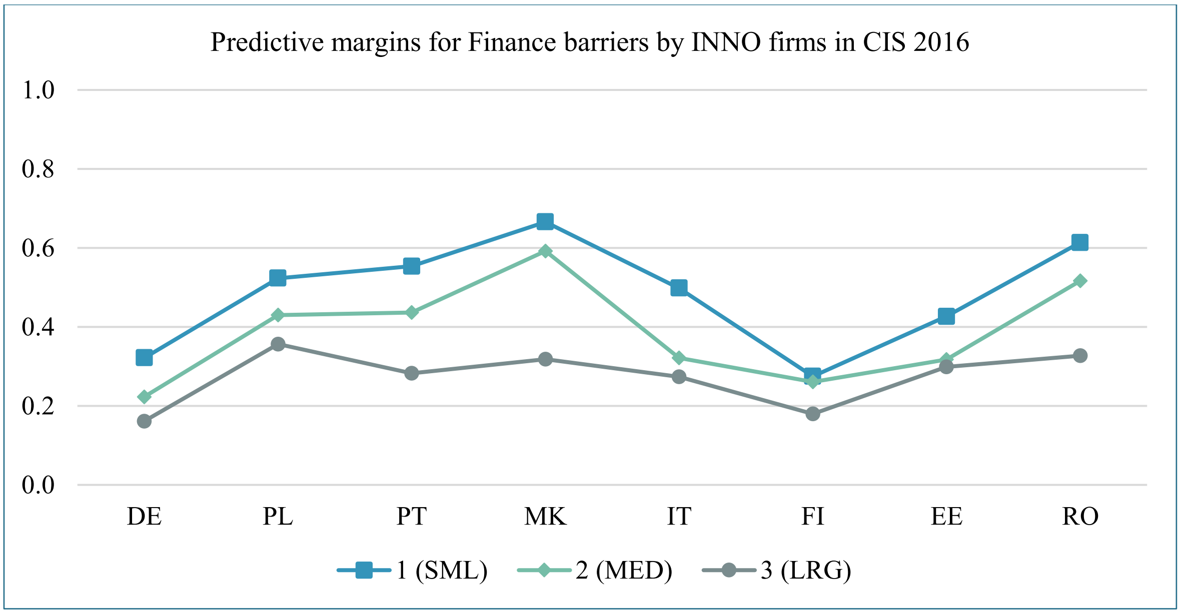


Figure 8. Predictive margins: Innovative firms assessing Finance barriers as highly important across size classes in different countries.

The detailed presentation in this chapter was aiming to identify the obstacles that are more important across company sizes, sectors, and innovativeness and to develop a discernible consensus on their relative importance. Ameliorating the impact of obstacles to innovation is essential at the firm level to improve performance and at the policy level to design effective interventions. Often firms attempting to enter the innovation arena for the first time are unaware of the relative importance of the obstacles they face and tend to imitate practices of innovative ones without paying attention to their relative size.

A better understanding of the relative importance of the barriers to innovation is also essential to drive policy interventions aiming to remove them. Such interventions are broadly aimed and often have limited effectiveness. The results of this study provide sufficient clues for more refined interventions, both internal (procedures) and external (policies) to the firm, targeting well-defined size segments as well as making fundamental distinctions between innovative and non-innovative companies.

6. Operational layer

While the addition of the socio-economic and cultural factors highlighted the key role of the firm-level characteristics in defining the obstacles to innovation, it also brought forward the need to scale up the analysis and focus on the *operational* environment in the form of socio-economic and cultural factors in which a firm operates.

It has been theorized that the innovation divide is cultural, in the sense that perceptions about innovation affect innovation performance innovation [15]. While this is often a circular argument (for instance, perceptions impact innovation performance and, at the same time, innovation performance is a key determinant of established perceptions), the existence of "psychological" barriers affecting innovation performance has been a persistently valid concern [89]. For instance, a top-down, hierarchical culture that induces fear of consequences and thus neutralizes curiosity has been shown to be detrimental to innovation [30].

The existence of cultural barriers to innovation has been offered as an explanation for the persistent lag in innovation rankings of Central and Eastern Europe countries in comparison to their Western Europe counterparts [29]. Indeed, while these formerly "Eastern Bloc" countries have made great progress in the last 30 years, their innovation development has been markedly inferior to that of the old member states of the EU. In principle, these countries show strong potential for innovation, with a highly educated workforce, a tangible legacy of applied research, and an enviable proximity to a range of markets. Clearly, though their economic growth while transitioning to a market economy has not been based on innovation. While many have been members (or associated members) of the EU for almost two decades and have profited from their integration into European networks and EU Framework programs, experts and statistics are still inconclusive on whether the gap between western and eastern countries has been narrowed [90].

To make own, informed decision on the gap between Eastern and Western Europe, the study proceeds further by utilizing CIS data to examine the perceptions of innovation between firms operating in the East and West fractions.

6.1. Operational environment across East-West axis

As a matter of choice, the analysis is based on a group of four countries with distinct socio-economic profiles and diverse institutional models of work organization: Germany, Poland, Portugal and North Macedonia. Continental Germany (with its corporatist model of development and high levels of labor productivity) and Mediterranean Portugal (with its mixed model of development and moderate levels of labor productivity) represent the original EU 12 members and the Eurozone; Poland, a later entry in the EU 25 (but not the Eurozone) represents former Eastern European countries; and North Macedonia, a candidate country for accession to the EU represents the Balkan countries [31].

In CIS 2016, 106,184 firms in Germany, 43,828 firms in Poland, 14,602 firms in Portugal and 2,400 firms in North Macedonia were polled on their perceptions of the obstacles to innovation. With roughly one of every four firms surveyed, the 167,000 firms in the sample form a rich and representative milieu of company sizes, sectors, and locales. The detailed descriptive statistics are presented in Appendix A and Appendix B (Table A1, Table B6, Table B11 and Table B29). (Percentages may not add up to 100 due to rounding.)

Thus, for all four countries, the distribution of the samples between SML, MED and LRG firms follows approximately a consistent 75%-20%-5% pattern which is fairly representative of the corresponding populations [88]. In Germany and Portugal, about 66% and 65% of the firms surveyed had introduced an innovation or had ongoing or abandoned innovation activities during the three years preceding the survey period (INNO firms). Only 38% of the firms surveyed in North Macedonia and 24% in Poland qualified as INNO under this criterion. Thus, as measured by the existent distribution of innovators and non-innovators, Western subject countries demonstrate a lesser innovation gap compared to the Eastern ones.

Next, regression analysis and predictive margins computation was conducted to measure the innovation gap (and cultural effects) in terms of innovation barriers. The detailed presentation of the predictive margins (and their statistical significance) across the selected countries are presented in Appendix A and Appendix B (Table A3, Table B8, Table B13 and Table B30).

The cumulative graph in Figure 9 (a) summarizes the predicted importance of the innovation barriers as perceived by the European "EAST" (Poland and North Macedonia) and "WEST" (Germany and Portugal), and demonstrates clearly that although "WEST" countries show lower predicted importance, the differences in the ranking of the various obstacles are minimal (mostly less than 10%). Distribution in Figure 9 (b) demonstrates that there are very few discernible differences regarding the ranking of the obstacles across the four countries. Indeed, there is no divide, but rather a palette of shades regarding perceptions of innovation that are entrenched in firm-level characteristics.

Specifically, firm size and sector of operation “color” the perceptions and in turn such perceptions moderate the inclination to innovate much more heavily than cultural issues.

As for the firms in different size classes or sectors, Figure 10 (a) and (b) demonstrate slightly more profound differences in the relative importance of the innovation barriers.

For instance, large-sized firms of “EAST” tend to perceive the barriers closely similar to the “WEST” firms. (The same importance of 27% is computed for U_DMND.) Similar comments can be made about “EAST” firms engaged in service industry.

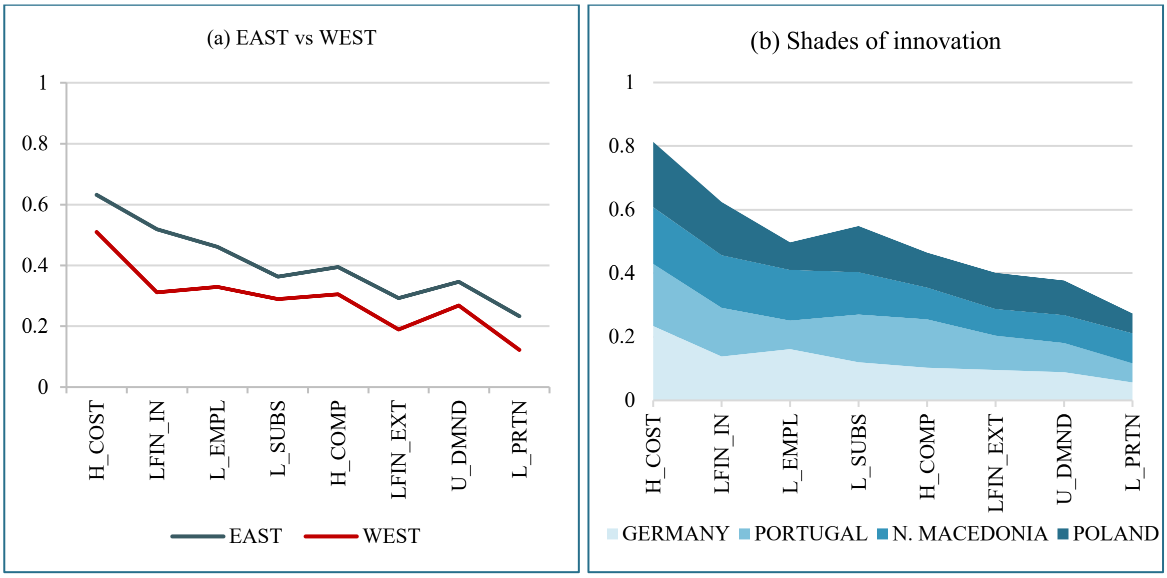


Figure 9. Ranking of obstacles across countries.

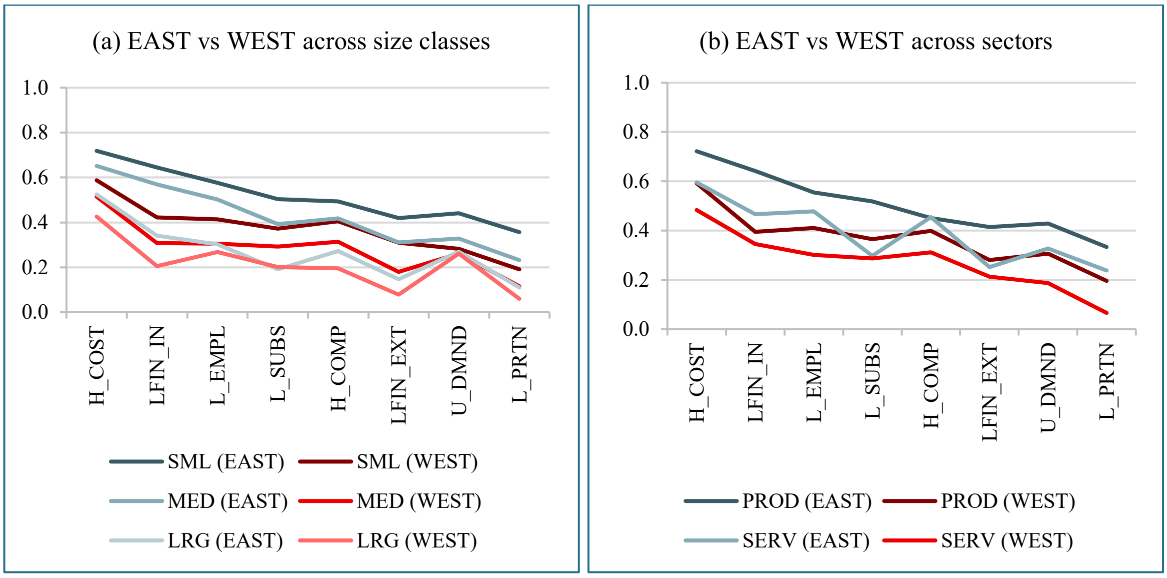


Figure 10. Ranking of obstacles across countries, size classes and sectors.

The results presented demonstrate that the argument of an alleged cultural divide being the cause for the East-West innovation performance gap is challenged. The view that perceptions about innovation differ substantially due to societal norms is certainly outdated for the countries examined. Firm-level discriminants appear to be broadly uniform across Germany, Poland, Portugal, and North Macedonia. The transition to a market economy and the knowledge transfer in a globalized world has certainly had an impact and it is difficult to discern an East-West divide at least within the context of the EU. Country-specific differences in perception appear to be the result of a diffusion of firm-level factors reflecting earlier observations on the issue [91].

6.2. Operational environment across the "Global North-South" axis

Exploring the argument that level of development of the country in which a firm operates impacts its innovation performance was advanced further by focusing on the conventional divide of the "Global South", that is the group of countries whose economies are not yet fully developed, and which face specific socio-economic challenges [32].

Indeed, innovation performance has emerged as a key factor distinguishing the Global South from the Global North countries [92]. For example, in Central Asia, an area representative of the Global South, the country-level innovation lag is ever present. Despite several national initiatives to provide tangible support for innovation over the last decade, innovation output unexpectedly regressed considerably in Kazakhstan [93]. The same downward performance is observed for Kyrgyzstan and Tajikistan [94].

To explain this paradox, it has been theorized that the reasons may include issues, ranging from cultural and gender to the digital divide. The explanations offered and the recommendations provided, however, often appeared to be disjoint from reality, seemingly reflecting prior biases rather than outcomes of evidence-based analysis of the situation [95,96].

Although the analysis in Section 6.1 detected no discernible East-West cultural divide in Europe, other than perhaps varying perceptions of innovation entrenched in firm-level characteristics [38], the gender dimension is more complicated. While women and men are equally productive in innovation and creative activities, work environments can discourage women's innovation. This gender gap is not equal across countries and industries, manifesting itself increasingly more prominently along women's career paths.

Gender equality in science is vital for the achievement of internationally agreed development goals, such as the 2030 Agenda for Sustainable Development of the United Nations. Alas, when the United Nations celebrated the International Day of Women and Girls in Science on February 11, 2020, the gender gap was painfully present despite global efforts over the past 15 years to inspire and engage women and girls in science. At present, only 29% of researchers worldwide are women, according to the UNESCO Institute for Statistics. Furthermore, numerous studies have found that women in science, technology, engineering, and mathematics fields publish less, are paid less for their research, and do not progress as far as men in their careers [97].

During the last decade, evidence has been collected on the positive impact of gender diversity on innovation performance. Gender diversity appears to increase the likelihood of introducing innovative products, services, processes and organizational changes, and corresponding patent filing activities [98–100]. In fact, the positive impact of gender diversity in R&D teams increases with the increased intensity of the tasks, or in conditions of intense market competition or uncertainty [101].

Analysis in this chapter reveals that one of the crucial determinants of the gender gap lies in the access to the digital resources necessary for innovation and the skills to utilize these resources. In a world where most jobs have a digital component [102], access to the requisite digital tools and training is not available for numerous stratums of the population, including girls [33,102]. This gender digital divide (as accessibility of digital resources across the gender) seems to correlate with the income levels of the economy when measured across countries.

For instance, according to [33] countries categorized as high-income report the highest levels of equal digital access, whereas low-income countries report the lowest. However, the situation is complicated further due to lack of sufficient data, and future verification on a grander scale is required.

One of the contributions of the thesis is a small exploratory study using primary data collected in Kazakhstan, a Global South country, and an exemplar of post-Soviet Central Asia [94].

Thus, the regression analysis and predictive margins computation was conducted on the data collected via an anonymized online questionnaire distributed to the R&D departments of 10 prominent manufacturing, construction, and oil & gas firms in Kazakhstan. (Detailed descriptive statistics of the sample are presented in Table C1 in Appendix C.) The firms were selected because they are on the avant-garde of innovation in

Kazakhstan and because their apparent internationalization is conducive to a progressive attitude on gender issues. Table 16 elaborates on the demographic description and presents the number of respondents by gender, revealing that the female response rate is generally higher than the male one.

Table 16. Gender distribution of the surveyed sample.

Sector	**Males surveyed**	**Male responses**	**Male response rate**	**Females surveyed**	**Female responses**	**Female response rate**
Manufacturing	75	39	52%	25	12	48%
Construction	132	39	30%	71	21	30%
Oil & gas	82	30	37%	36	28	78%
Total	**289**	**108**	**37%**	**132**	**61**	**46%**

Male employees contributed 64% of the responses (108 out of 169) and female employees contributed 36% (61 out of 108), in very close proportion to the gender ratio in the corresponding departments. The highest response rate was recorded for the oil & gas industry with an impressive 78% of addressed females responding to the questionnaire. For the other two sectors, there was an apparent parity in the gender distribution of the response rate. Overall, the received questionnaires exhibited a gender distribution that approximated reasonably well the percentage of male and female participants and respondents across industries and the totality of the sample.

The survey recorded the perceptions of R&D specialists on the role of the gender-diverse teams in several activities of the company, as well as the distribution of the digital skill across the genders. Specifically, the respondents were asked to score their position on whether the gender-diverse teams drive the implementation of innovative products and services in the company and launch the business activities that enhance innovation productivity in the company. Additionally, their perceptions on whether women in the company have the same digital skills and digital know-how as men were recorded.

In contrast to CIS data, the sample was categorized across two size classes (medium and large) and three sectors (manufacturing, construction, and oil & gas). While the computed predictive margins (and their statistical significance) are summarized in Appendix C

Exploring additional determinants of innovation. Figure 11 reflects the predicted level of gender diversity in companies' operations and of level of digital skills across the gender.

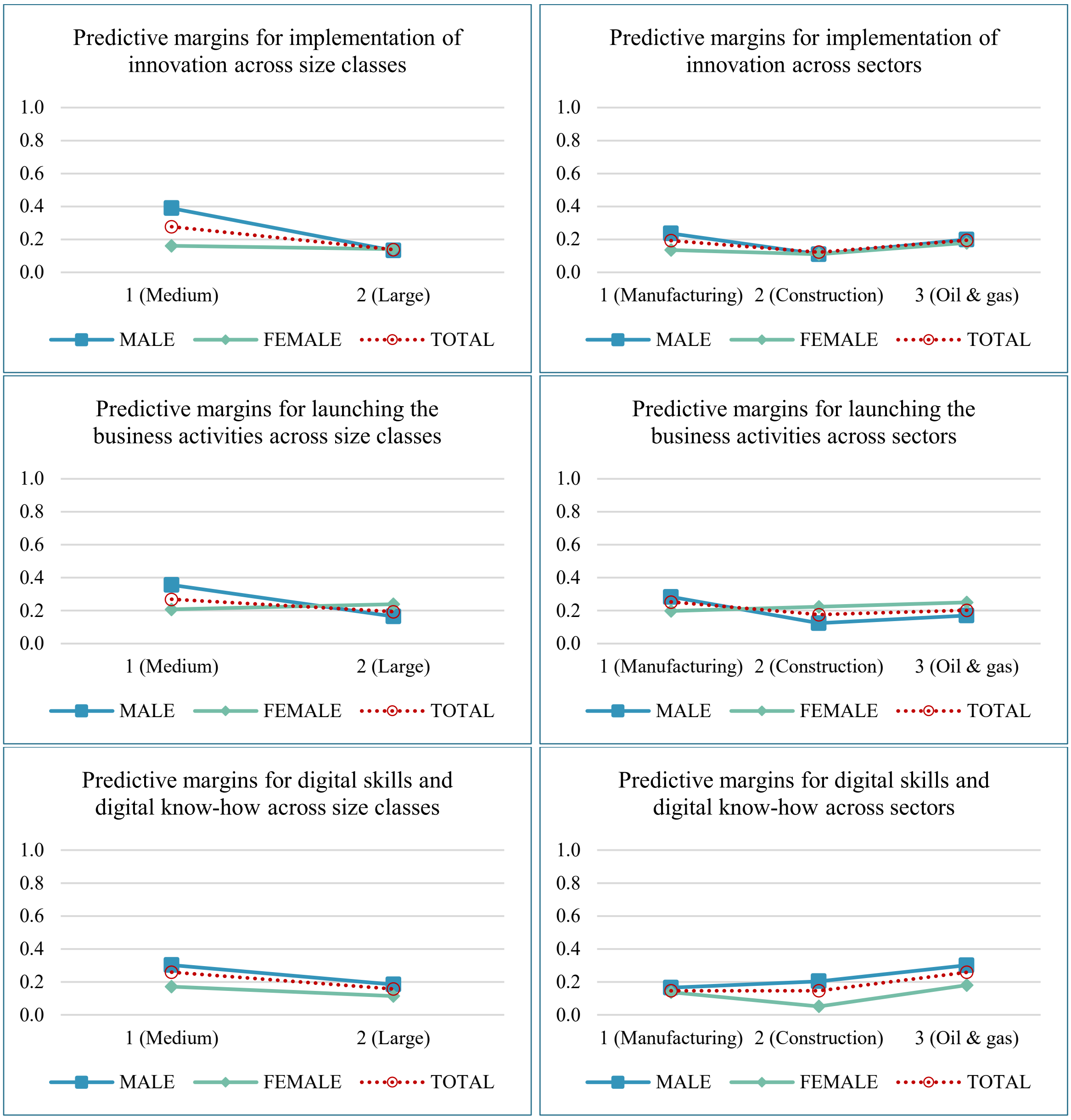


Figure 11. Predictive margins: Firms assessing the role of gender-diverse teams across size classes and sectors.

Thus, male employees tend to report higher involvement of gender-diverse teams, especially in medium-sized firms. In fact, gender-diverse teams driving the implementation of innovation in the company are reported by 39% of males compared to twice lower 16% of females. Interestingly, the opinions in large firms are not that differentiated. Moreover, female employees provide a better view of gender diversity than males on the involvement of gender-diverse teams in and launching the business activities that enhance innovation productivity in the company.

Granularization across the sectors of operation does not introduce new patterns in estimated gender diversity in the described two operations, which cannot be said about the digital skills. For instance, employees in different sectors demonstrate different opinions on the level of digital skills and digital know-how possessed by females and males.

In general, the low part of Figure 11 reveals that only 22% of the male and 12% of the female respondents appear to believe that women in their team have the same digital skills and digital know-how as men. Across the board, females provide a much dimmer view of women's digital skills. The situation appears to be better in medium-sized firms compared to large ones (26% vs 16%) and in oil & gas compared to manufacturing and construction (26% vs. 15%).

Addressing gender diversity as an important determinant of the innovation gap the analysis in this chapter confirmed two main beliefs or notions.

First, the analysis of the globally "southern" country such as Kazakhstan supports the observation that countries categorized as high-income report the highest levels of equal digital access, whereas low-income countries report the lowest [33]. The gender gap in innovation is apparent in Kazakhstan, and the results of this exploratory research confirm it succinctly. Minor variations across firm sizes and sectors do not disguise an overwhelmingly troublesome image of gender disparity in the teams implementing and supporting innovation in the country.

Secondly, this study addresses one of the main composites of the gender gap itself - the inequality in access to digital resources across gender- which makes its results far more interesting and far more important for the digital transformation of Kazakhstan.

Digital transformation, the adoption and integration of digital technologies into all areas of business, provides new opportunities for the economic empowerment of women and can contribute to greater gender equality. As innovation activities are at the core of the digital transformation, greater inclusion of women in the digital economy can have tangible economic and social value. Yet, women are under-represented in digital technologies jobs, with men being four times more likely than women to be digital technologies specialists [103].

While Kazakhstan has an enviable record of universal access to mobile telephony and the internet, the gender digital gap is persistently present. What is noteworthy is that an overwhelming majority of women scientists in the R&D departments of some of the most progressive and technologically advanced firms in the country do agree that men in their workplace have far better digital skills and digital know-how than women.

This almost universally held belief cannot be explained by asymmetries in accessing digital technologies and creates a great impediment in addressing the gender digital gap. It may very well be that such a belief is not necessarily a reflection of reality. For instance, women may be better endowed with digital skills; skills that are in "effect" unobservable because of a priori discriminatory views of men and women in the workforce.

Based on this observation, it can be posited that a "residual" of the gender digital gap may be attributed to factors coming from within. Female scientists may need to be convinced to shed a possible unconscious bias and take a more active role in digital transformation. In fact, it appears that this may be a case of the "impostor syndrome", the intense feeling of inadequacy despite a record of successes.

To summarize, the gender analysis in this chapter sought to integrate two independent constructs, gender diversity in innovation and the gender digital gap, in a novel coherent theme. By illuminating previously unaddressed dimensions of the gender digital gap, such as the impostor syndrome, it illuminated antecedents and moderators of the innovation paradox of Kazakhstan. While this was a perception-based pilot study focusing on eliciting the beliefs of innovation workers, the strength of some of the outcomes provides a solid basis for future research.

7. Process layer

The innovation process is a multi-dimensional construct, yet the dimensions of innovation are not limited to “static” internal (firm-layer) or external (operational layer) characteristics and parameters of the executors. The complexity of innovation is also expressed in its dynamic, constantly evolving nature. The actual *processes* of innovation are addressed separately in this chapter with the focus shifting away from perceptions about innovation to tangible innovation outputs, such as IPRs.

7.1. Knowledge acquisition and management processes

As innovation is universally defined as the process of finding and using new ideas, innovative firms develop competitive advantages through knowledge acquired externally or developed internally, and its management, exploration, and exploitation. Thus, the first part of the process layer analysis focuses on the knowledge acquisition and management processes in the firms, by utilizing the CIS responses on the knowledge sourcing and innovation expenditures from 54,000 German innovative firms [104].

Descriptive statistics on the sample are presented in Table 17. Thus, the distribution of the firms across the sample is slightly skewed away from SML firms (65%) and increasingly towards MED (27%) and LRG firms (8%). Regarding the sector of operation, the focus is on the manufacturing and information & communication firms, which constitute three quarters of all innovative firms in Germany (54,000 out of almost 70,000 INNO firms).

Table 17. Descriptive statistics of the Germany sample from CIS 2016, innovative firms in manufacturing and information & communication.

DE 2016	Surveyed firms	Percent of total firms
Size class:		
SML	35,571	65%
MED	14,794	27%
LRG	4,217	8%
Total Size class	**54,582**	**100%**
Sector:		
MANUFG	44,447	81%
INFOCOM	10,135	19%
Total Sector	**54,582**	**100%**

Nevertheless, the firms were asked to assess the importance of various sources of knowledge and types of innovation expenditures on the 4-point Likert scale. Following the methodological rules described in Chapter 3, their lists with the coded names are summarized in Table 18 and

Table 19 of dependent variables.

Focusing on the knowledge sources, specifically the ratio of the firms which express a certain opinion on the high importance of each source, Figure 12 shows the percentage of the High assessment votes. The actual numbers are presented in Appendix A (Table A7).

From the diagram, it is apparent that GROUP and PRIVT are the top two sources in terms of importance. COMPT and FAIRS form the second group of importance, while all other sources received 5% of the votes or less. There is surprisingly little difference across

Table 18. List of knowledge sources for innovation in CIS 2016.

Classification	Code	Explanation
Internal	GROUP	Enterprises within the enterprise group
Market	SUPPL	Suppliers of equipment, materials, components, or software
	PRIVT	Clients or customers from the private sector
	PUBLC	Clients or customers from the public sector
	COMPT	Competitors or other enterprises of the same sector
	CONSLT	Consultants or commercial labs
Institutional	UNIVS	Universities or other higher education institutions
	GOVRN	Government or public research institutes
	RESIN	Private research institutes
Other	FAIRS	Conferences, trade fairs or exhibitions
	PRINT	Scientific/technical journals or trade publications
	ASSOC	Professional or industry associations

Table 19. List of innovation expenditures in CIS 2016.

Code	Explanation
INT_RD	R&D activities undertaken by the firm to create new knowledge, including software development in-house that meets this requirement
EXT_RD	R&D activities contracted to other firms (include enterprises in the same group) or to public or private research organizations

EXT_KN	Acquisition of existing know-how, copyrighted works, patented and non-patented inventions, etc. from other firms or organizations

company sizes with LRG firms emphasizing GROUP slightly less and COMPT slightly more compared to SML and MED firms. These ±3% differences are of course insignificant within the broader context.

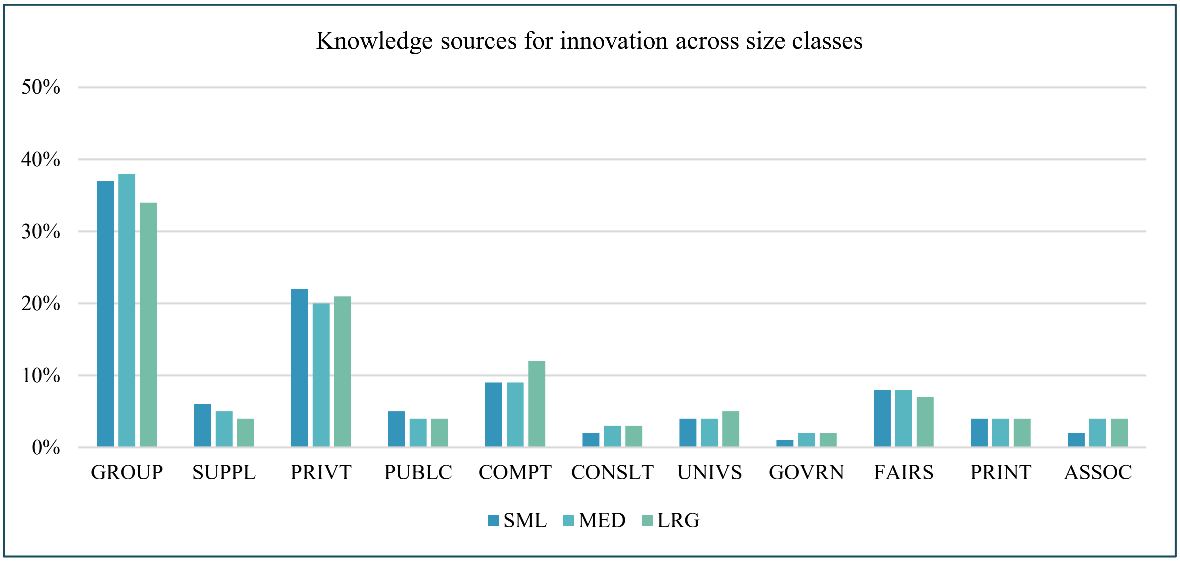


Figure 12. Knowledge sources for innovation ranked in terms of importance across size classes (votes cast).

As for the sectors of operation, due to the data specialties, the sectors were defined as Manufacturing (MANUFG) and Information & Communication (INFOCOM). Figure 13 it is apparent that in this case as well there is no discernible difference between the two sectors the characteristics of the firms of which diverge significantly. MANUFG firms emphasize PRIVT slightly less and FAIRS slightly more compared to INFOCOM firms, but the differences are less than ±5%. The actual numbers are presented in Appendix A (Table A9).

The fundamental conclusion from this part of the analysis is that innovative firms in Germany obtain their knowledge for innovation internally or from enterprises within the enterprise group (37%) and externally from their clients or customers from the private sector (21%). Secondary sources are competitors or other enterprises of the same sector (9%) and conferences, trade fairs or exhibitions (8%). Every other source is listed at less than 5%. This ranking of the sources of knowledge is quite robust across firm sizes and sectors.

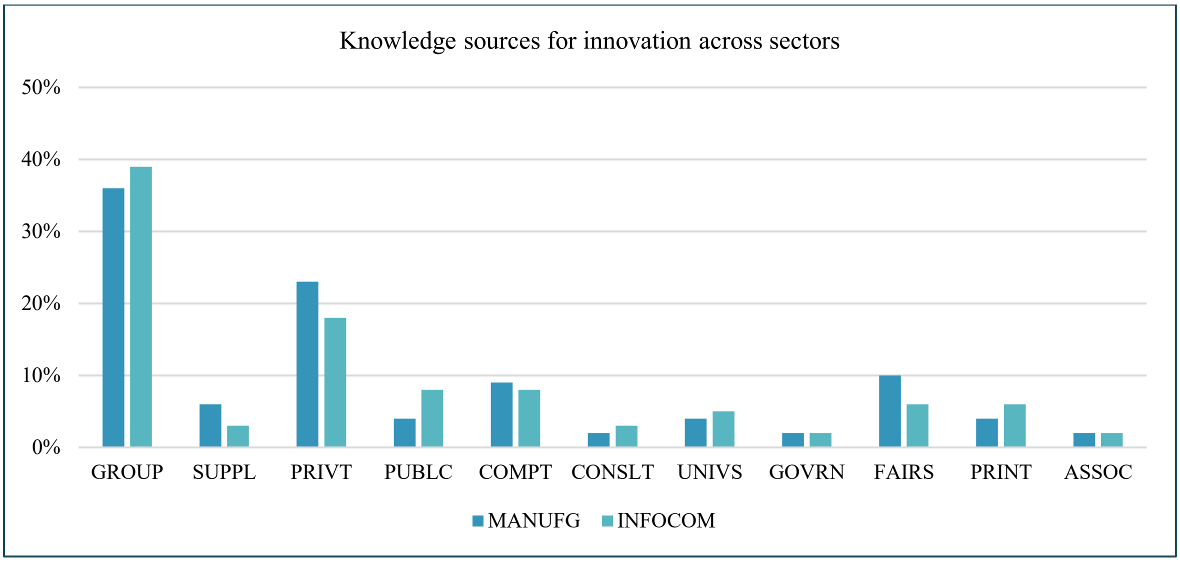


Figure 13. Knowledge sources for innovation ranked in terms of importance across sectors (votes cast).

The results for the expenditures on internal and external innovation and knowledge acquisition are summarized in Figure 14. It is apparent that irrespective of size, these firms devote an impressive 82% of their innovation expenditures to internal R&D activities and a mere 12% and 5% to external R&D and to the acquisition of external knowledge. In the case of sectors, both sectors devote about 80% of their expenditures to internal R&D. there MANUFG firms tend to emphasize external R&D over the acquisition of external knowledge while INFOCOM firms split their external expenditures almost evenly between them.

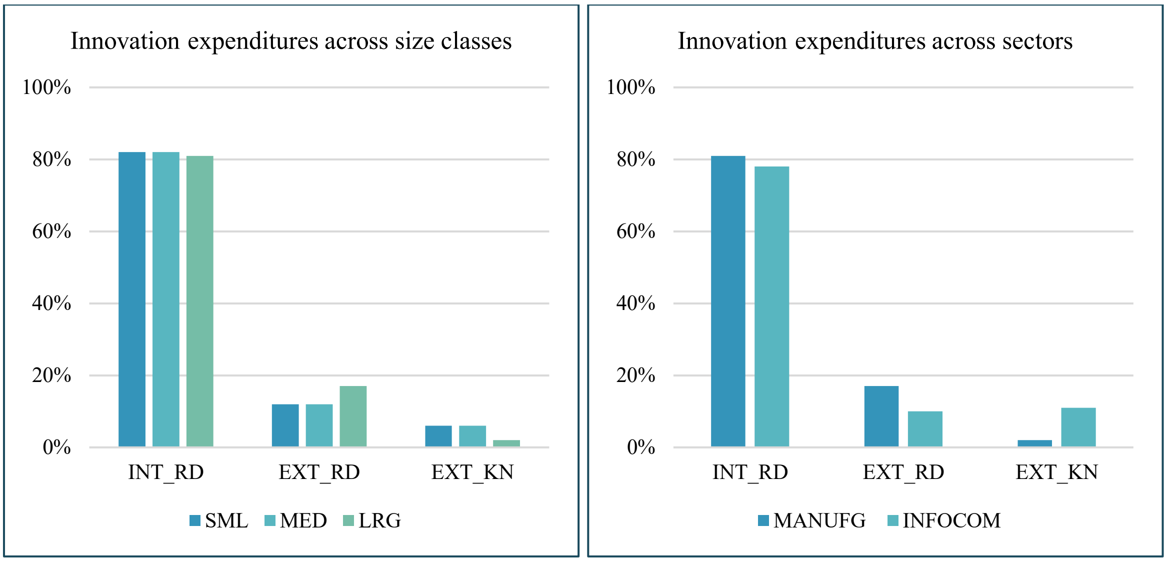


Figure 14. Innovation expenditures across size classes and sectors.

In summary, a clear picture emerges naturally from the analysis of these two parts. Thus, despite the multitude of available knowledge sources for innovation, innovative firms depend mostly on internal sources (including enterprises within the enterprise group) and to a much lesser extent on market sources (primarily clients or customers from the private sector). This observation is further amplified by the fact that the lion's share of innovation expenditures is devoted to internal R&D with very limited resources targeting external contract research or outright acquisition of knowledge from third parties.

Figure 15 illustrates succinctly the outcomes of the analysis, which are true across the board and are not mediated in any meaningful way by firm size or sector. The insularity in the acquisition of knowledge is deeper, considering that 82% of innovation expenditures do *not* include enterprises in the same group. (Resources devoted to R&D performed by other firms in the same group are counted in the external R&D expenditures.)

This insularity is puzzling considering that German firms are at the forefront of innovation, having significant resources to expend and operating in a modern, fully networked environment that is conducive to efficient information flows.

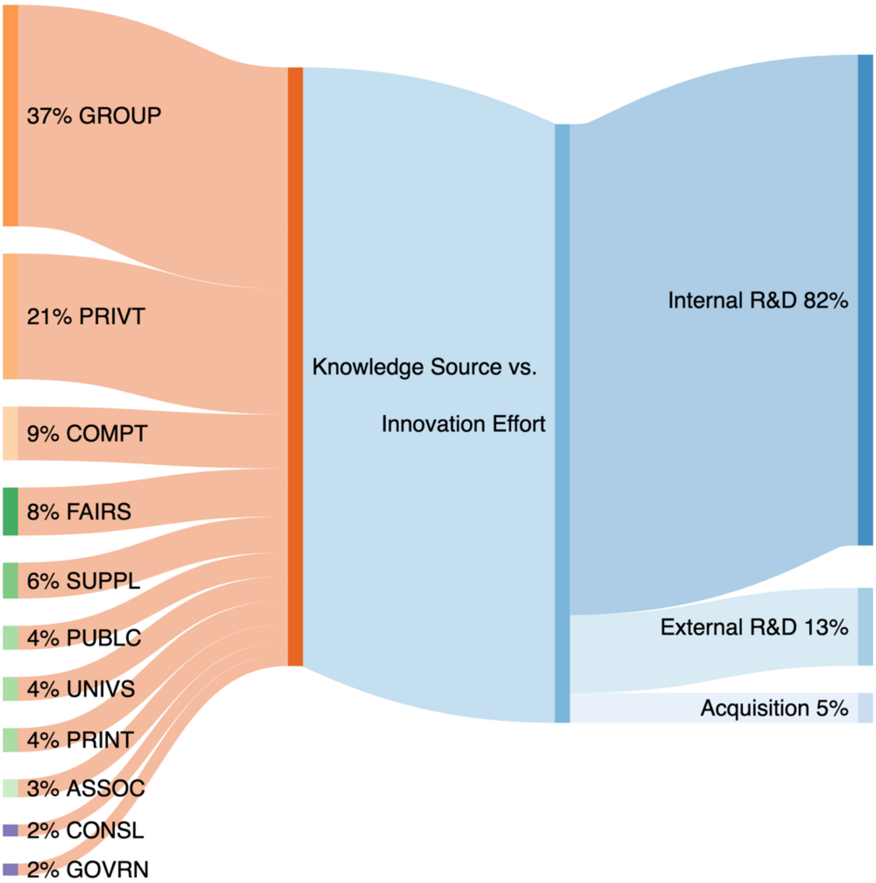


Figure 15. Sankey diagram of knowledge sources for innovation vs innovation expenditures.

7.2. Protecting innovation output processes

The process-oriented perspective and recent results on the important role of internal resources within the firms led to a re-examination of the firm-level analysis conducted in Chapters 5 and 6. More precisely the impact of the firm size on their propensity to innovation is revisited from the point of view of actual IPRs produced, from patents and trademarks to trade secrets and copyrights. Considering the exploratory nature of the study and to avoid congestion, the Germany CIS 2016 sample is limited to the largest sector category (thus manufacturing firms (MANUFG)) with an emphasis on their prior engagement in innovation activities [105].

For instance, impressive 70% of the surveyed manufacturing firms claim themselves as innovative. While the relative ratio of SML, MED and LRG firm size classes in the total sample is fairly representable of the size distribution of German manufacturing firms [2] (approximately 12:4:1), the same ratio in the subset of INNO firms is skewed to 7:3:1. This is due to the fact that an overwhelming 93% of the large-sized firms are INNO while the same percentage drops down to 80% for MED firms and to 64% for SML firms (Table 20).

Table 20. Descriptive statistics of the Germany sample from CIS 2016, manufacturing firms.

DE 2016	Surveyed firms	Percent of total firms	Surveyed INNO firms	Percent of total INNO firms	Percent of INNO firms in a category
SML	43,777	69%	28,158	63%	64%
MED	15,564	25%	12,504	28%	80%
LRG	4,068	6%	3,785	9%	93%
Total	**63,409**	**100%**	**44,447**	**100%**	**70%**

Addressing the IPRs related activities in the firms, in the CIS survey the manufacturing firms were asked if they applied or registered for protectable IPRs during the three years preceding the survey period. Interestingly, CIS reports the number of firms that engaged in just one type of IPRs during the survey period, which are summarized in Table 21. The aggregated term “Any IPRs” is not the sum of the other variables, but the number of firms that engaged in at least one type of IPRs related activity.

Based on Table 21 seven dummy variables were thus created as dependent, so, each of the dummy variables is binary depending upon whether the firm reported the corresponding activity (1) or not (0). Following the procedure described in Chapter 4 predictive margins (i.e the predicted probabilities of the firms applying, registering or using the certain IPRs) were computed and graphically represented in Figure 16 for innovative firms and in Figure 17 for non-innovative firms. The actual results in tabular form are presented in Appendix A (Table A5).

Table 21. List of IPRs in CIS 2016.

Variable	Explanation
Patent	Enterprises that applied for a patent
Trademark	Enterprises that registered a trademark
Utility model	Enterprises which applied for a utility model
Industrial design	Enterprises that registered an industrial design right
Trade secret	Enterprises which used trade secrets
Copyright	Enterprises which claimed copyright
Any IPRs	Enterprises which applied for/registered/claimed any IPRs

These breakdowns across the firm size demonstrate that the propensity of a firm for specific forms of IPRs is indeed moderated by its size and innovativeness. As expected, INNO manufacturing firms are more involved in inventive activities leading to protectable IPRs than NON-INNO ones.

Surprisingly though, NON-INNO manufacturing firms are also engaged in such activities at quite a significant level. It was noted that this could be the outcome of inventive activities outside the three-year window or accidental discoveries outside the purview of a defined innovation project. The greater affinity of NON-INNO firms for lighter forms of IPRs, and not patents, lends additional weight to this hypothesis. Another possible mediating factor could be that a number of NON-INNO firms are transitioning to the INNO category and their involvement with single IPRs is a sign of their trajectory. These central trends are valid across all firm sizes, but they are differently nuanced for INNO and NON-INNO firms.

For manufacturing firms in the INNO category, the probability of being involved in IPRs related activities rises significantly with firm size for all forms of IPRs recorded. The differential is largest in Patents where a LRG firm is 3.5 times more likely to report patent activity than a SML firm.

The results of this study demonstrate that large manufacturing firms remain the dominant players in the invention, protection and commercialization of new technologies. It is apparent that the ability of many small firms to successfully engage in innovation is hampered by their lack of resources, and by their limited ability to assess risk [106,107].

Thus, the majority of small and medium enterprises (SMEs) remain technology followers [108]. There is a significant minority though of technology developers or new technology users that play a key role in the early stages of new technological inventions and their validation. When SMEs protect their inventions, they prefer trade secrets as they expect fewer benefits from patents compared to large firms and they cannot afford the pressure of high litigation risk associated with patenting [109,110].

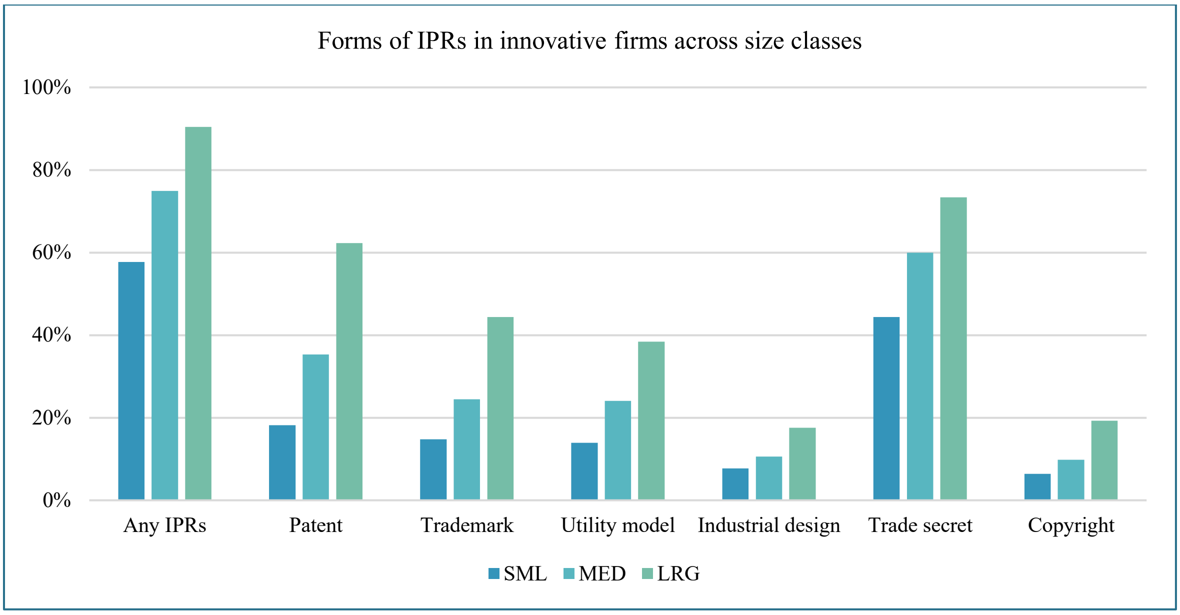


Figure 16. Forms of IPRs reported in innovative firms across size classes.

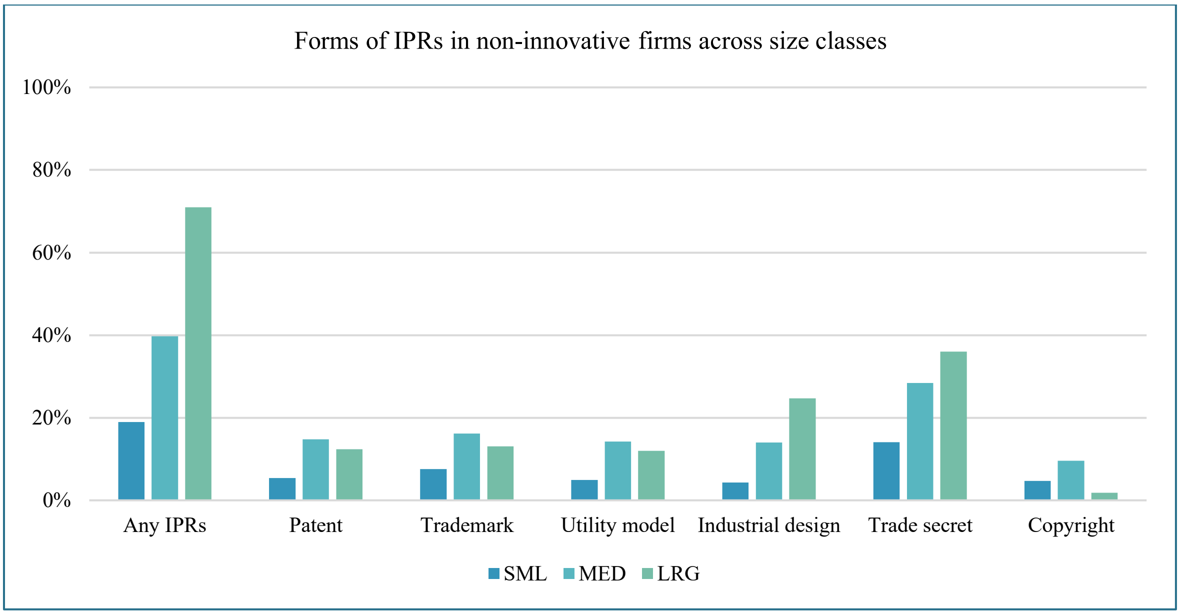


Figure 17. Forms of IPRs reported in non-innovative firms across size classes.

This outcome amplifies better the observation that firm size matters which emerged in the study of Chapter 5 and creates an argument for the adoption of IPRs as a better reflection of the situation than the surveys of perceptions about innovation in the bulk of the CIS data. Thus, Figure 16 and Figure 17 capture succinctly the differences in the preferred modalities of IPRs related activities for INNO and NON-INNO firms across firm sizes. In all cases, the prevailing forms of IPRs protection are Trade secret and Patent, which have distinct signaling and protection characteristics.

It should be noted that a patent grants an exclusive property right to the inventor for a limited period of time in exchange for disclosure of the innovation. A patent must reflect a technological novelty, be inventive and susceptible to industrial application. In general, patents signal a firm's innovation capabilities by showing that the firm possesses an invention or technology that is worth being protected.

Trade secret on the other hand refers to business information that is not known or readily accessible by the relevant public and has commercial value because it is secret. Trade secret protection is primarily governed by contract law, no specific novelty or originality is required, and there is no time limit.

7.3. Diversity processes in innovation hotspots

Finally, this chapter concludes with a more in-depth analysis of the processes inside the gender issue observed on operational layer in Chapter 6. Despite the identified crucial role of gender diversity in innovation success, the analysis is hindered by the paucity of data-driven studies. Surveys of executive perceptions, simulations under controlled conditions and field research through proxy metrics point to a positive relationship between diversity and innovation but suffer from significant limitations.

Since innovators are almost invisible in innovation research, to alleviate this complication this study addresses the issue of gender in innovation through an analysis of patent application data, which are direct -although not fully complete- metrics of innovation output as they (mostly) capture technological innovations.

Specifically, the analysis is based on patent application activities coming from geographical regions with intense innovative activity. WIPO introduced a coherent methodology to identify innovation hotspots based on their patent activity and showcased it as a special section in its Global Innovation Index 2017 report [78].

The methodology is based on patent application data of the PCT which account for more than 98 percent of patent filings worldwide. PCT data are considered high quality because they are collected based on uniform filing standards. Seeking an international PCT patent is a costly and lengthy process, to be followed only when there is a reasonable expectation of a sufficiently high return. Thus, PCT data are more likely to capture the most commercially valuable inventions. On the downside, not all international patent applications go through the PCT system, and not every PCT application will eventually result in a granted patent.

Thus, data from the WIPO 2017 report are used because they include the share of women inventors among all inventors located in a particular hotspot (Table 22). (Subsequent editions of the annual WIPO report omit this very important information.) The analysis includes the 31 top innovation hotspots in the US, and for each hotspot, the following pieces of information are included:

- Total number of PCT filings (PCTF);
- Share of women inventors (WI); and
- Total population of the geographical area (POP).

The primary objective of this analysis is to measure the effect of gender diversity, as measured by the share of women investors (WI) on the innovation productivity of a given innovation hotspot, as measured by its total number of patent filings (PCTF), while controlling for the possible moderating effect of the total population of a hotspot's area (POP) [111].

All the analysis was performed with the open statistical software package *jamovi* [112]. Descriptive statistics of the variables, as well as the Shapiro-Wilk test are presented in Table C5 in Appendix C.

Thus, patents from top USA innovation hotspots list, on average, 14.7% of women inventors with the range extending from 9.2% to 20.7%. For comparison, the USA Patent and Trademark Office (USPTO) estimated the number of patents with at least one woman inventor for the same time period at 20% -for the entire USA, not just hotspots.

The Shapiro-Wilk test indicates that there is no significant departure from normality for WI ($p>0.05$). PCTF and POP on the other hand fail the normality test with 95% confidence that the corresponding data do not fit the normal distribution.

Table 22. Top innovation hotspots in the USA*.

Rank	Innovation hotspot	Total filings	Women inventors (%)	Area population
1	San Jose–San Francisco, CA	34,324	15.0	6,056,626
2	San Diego, CA	16,908	16.9	3,552,659
3	Boston–Cambridge, MA	13,819	17.4	4,029,151
4	New York, NY	12,215	20.0	15,539,937
5	Houston, TX	9,825	11.6	5,227,899
6	Seattle, WA	8,396	13.2	2,315,154
7	Chicago, IL	7,789	13.1	5,777,498
8	Los Angeles, CA	5,027	15.0	11,851,722
9	Minneapolis, MN	4,422	12.1	2,545,762
10	Portland, OR	4,146	14.0	2,073,296
11	Irvine, CA	3,965	12.7	866,871
12	Philadelphia, PA	3,172	19.6	4,023,359
13	Plano, TX	3,147	11.9	3,763,640
14	Raleigh–Durham, NC	2,775	15.7	1,554,250
15	Washington, DC	2,491	19.4	3,369,256
16	Cincinnati, OH	2,481	14.6	1,776,679
17	Atlanta, GA	2,162	19.0	2,529,174
18	Austin, TX	2,089	9.2	1,492,160
19	Wilmington, DL	2,046	15.5	70,644
20	Indianapolis, IN	1,596	16.0	1,982,531
21	Hartford, CT	1,540	9.7	1,240,483
22	Rochester, NY	1,414	15.4	816,263
23	Phoenix, AZ	1,378	13.0	2,707,525
24	Cleveland, OH	1,346	11.2	1,385,879
25	Boulder, CO	1,319	14.4	2,806,543
26	Salt Lake City, UT	1,293	10.8	1,638,476
27	Ann Arbor, MI	1,289	14.1	620,199
28	Pittsburgh, PA	1,283	14.0	1,399,419
29	Albany, NY	1,184	13.0	749,001
30	St. Louis, MO	1,138	17.4	1,422,096
31	Baltimore, MD	1,089	20.7	2,861,888

* *adapted from* [78]

The correlation matrix in Table 23 reveals that there is a statistically significant correlation between the population in a hotspot area and the total patent productivity of the hotspot, a somewhat intuitive outcome. On the other hand, there is a weak positive correlation between the % of women inventors and the total patent productivity of a hotspot. This correlation however does not appear to be statistically significant.

Table 23. Correlation matrix.

		PCTF	WI
WI	Pearson's r	0.134	
	p-value	0.472	
POP	Pearson's r	0.447*	0.346
	p-value	0.012	0.057

* *significant at 10%;* ** *significant at 5%;* *** *significant at 1%*

The value of statistically insignificant results in socio-econometric studies has led to numerous debates and discussions [113,114]. It is the authors' firm belief that non-significant results are just as important as significant ones and should be duly reported to avoid contributing to underreporting bias. In fact, the absence of statistical significance does not necessarily imply the absence of the effect in a question. It may also indicate that the data are inconclusive either way or that the dataset employed is underpowered to confirm the effect observed.

Nevertheless, putting together an innovation team is the most challenging job for an organization, but one that is often conducted in an ad hoc manner. Individual innovator profiling is still a puzzling issue in innovation, but gender diversity is certainly a desirable team characteristic. Yet women inventors are strongly under-represented in almost every country around the world [115]. The consensus in the literature [111] is that the underrepresentation of women in the IPRs system is due to reasons such as the lack of access to financial and knowledge resources; the lack of understanding of the value of IPRs; the limited exposure to female inventor role models; and the broad discriminatory socio-cultural norms and expectations. Further, the limited availability of gender-sensitive data in innovation limits the ability of policymakers to develop and implement data-driven initiatives. In addition, the limited availability of sex-disaggregated data and other gender-sensitive indicators hampers the ability of policymakers and practitioners of IPRs to better understand the breadth and depth of the IPRs gender gap.

The exploratory study in this chapter is an attempt to help in this direction. The results demonstrate that adding a gender perspective is directly related to innovation performance as measured by patent applications. The quite modest effect observed requires further study with an expanded dataset.

8. Policy layer

8.1. Policy interventions aiming innovation hotspots

The comprehensive methodology of WIPO to capture the hotspots with a high concentration of innovation activities brings forward an additional important facet of the innovation gap worldwide. Thus, as it was mentioned, 77% of the patent filings from global innovation hotspots are emerging from just five countries – USA, Japan, China, Germany, and France [1].

This thesis addresses the innovation hotspots, also called industrial clusters, since besides highlighting the gap, as innovation agents in Industry 4.0 they may provide new insights into what determines the innovation performance of such clusters and the reasons behind the gap [1]. The concept of clusters has grasped the imagination of policymakers and proved extremely popular with governments eager to develop policies to promote innovation. Indeed, the industrial cluster is a perfect example of economic agglomeration, the tendency that is of firms in a particular field to concentrate geographically to achieve economies of scale and scope. Key in this concept is the hypothesis that when enough resources and competencies amass to reach a critical threshold in a geographical location, this confers a sustainable competitive advantage over other places in a given economic activity.

Even though it has not been conclusively proven that clusters invariably boost business performance and local development [34–36], the popularity of the cluster concept amongst policymakers remains intact.

Over the years, the concept of clusters has evolved to include diverse types of agglomeration (from local productive systems to industrial districts and business networks), yet a globally accepted definition of clusters remains elusive. Admittedly though, a large part of the popularity of clusters lies in the vagueness and definitional elusiveness of the concept [116]. It is precisely this ambiguity that allows both to apply the cluster concept to different realities and to prevent an accurate policy evaluation [117].

In the era of Industry 4.0, where small and medium-sized firms increasingly have to compete internationally [118], clusters can play an important role in supporting firm competitiveness by increasing productivity, innovation and firm formation and providing spillover effects to their entire geographical region. Indeed, clusters have become a worldwide fad primarily because they have been associated with innovation and the knowledge economy [119]. Most national innovation systems and policies from industrial districts to science parks and university research include clusters as an integral part of their arsenal. The evidence though of a positive association between clusters and innovation capacity is not consistent [120,121] and questions have been raised on whether clusters help a firm's knowledge creation in Industry 4.0 [122].

The problems present in defining clusters, assessing their performance and developing coherent, evidence-driven policies are real. The primary challenge for cluster management is how to leverage innovation to benefit the firms in the cluster as well as the geographic region as a whole. As the clustering effect evolves from mere economic agglomeration into an innovation agent, it is important to focus on ways to leverage this potential for development. The key challenge is of course to be able to identify the themes, the sectors and the actors that will make such leveraging successful.

The observation of emerging spatial data on innovation has shown that innovative activities tend to be concentrated in clusters linked to a single city or a set of neighboring cities [123]. Adopting such a cluster view of innovation opens the door to a better understanding of the local dynamics of innovation. Innovation hubs at the city- or regional-level tend to be drivers of innovation performance deserving in-depth analysis. Unfortunately, gaining empirical insight into the comparative performance of individual innovation clusters is challenging. There is neither a generally accepted definition of what constitutes an innovation cluster nor a correspondence of innovation clusters with geographical units for which statistical data are routinely collected.

Seeking to overcome these challenges, WIPO recently released a working paper identifying the world's top-100 innovation clusters based on their patent activity [37]. Specifically, the report overviews over 950,000 patent applications published under the PCT System between 2011 and 2015. The small excerption the data is presented in Table 10 and the full list of the clusters is presented in Table C6 in Appendix C. Nevertheless, the resultant dataset provides information on cluster performance within and across countries in a systematic, data-driven way.

To address the variation in the output of large and small clusters, the data were normalized over the total cluster output, and the following three metrics were defined:

- DOM = Top entity filings / Total cluster filings (%);
- SPE = Top sector filings / Total cluster filings (%); and
- PRO = Total PROs filings / Total cluster filings (%).

representing respectively the degree of DOMinance of the top firm in the cluster; the level of SPEcialization in the cluster; and the relative contribution of PROs in the cluster.

The data were analyzed with XLSTAT and the following three tables detail the descriptive statistics of these three variables; the correlation matrix with the p-values (Pearson); and the multicollinearity statistics [124].

Table 24. Correlation matrix of the normalized variables.

Variables	DOM	SPE	PRO
DOM	1***	0.552***	-0.077
SPE	0.552***	1***	-0.319***
PRO	-0.077	-0.319***	1***

[*] significant at 10%; [**] significant at 5%; [***] significant at 1%

From Table 24, it can be observed that there is some degree of positive correlation between the variables DOM and SPE and some degree of negative correlation between the variables SPE and PRO. The first observation is almost intuitive in the sense that the presence of a dominant firm in a cluster is expected to increase the specialization within the cluster. The second observation, that in a specialized cluster the contribution of public research entities is somewhat diminished, is less so.

Table 25. Multicollinearity statistics of the normalized variables.

Variables	DOM	SPE	PRO
R^2	0.316	0.382	0.116
Tolerance	0.684	0.618	0.884
VIF	1.461	1.617	1.131

The question of whether the degree of correlation between these variables is high enough to cause problems when fitting and interpreting a regression model is addressed in Table 25. Indeed, the multicollinearity metric, known as the variance inflation factor (VIF), which measures the correlation and strength of correlation between the explanatory variables has a value close to 1 for all three variables. This implies multicollinearity is not a problem, in the sense that the moderate correlation detected between these three variables is at a level that is not high enough to warrant additional attention.

A linear regression model is then constructed to predict the total number of patent filings of a cluster with the regressor variables DOM, SPE and PRO:

$$T = \beta 0 + \beta 1\,(DOM) + \beta 2\,(SPE) + \beta 3\,(PRO) \tag{9}$$

where the regression coefficients β_0, β_1, β_2 and β_3 are computed in Table 26.

Table 26. Model parameters.

β	Value	Std. Error	t	Pr > |t|	L-bound (95%)	U-bound (95%)
β0	7,950	2,728	2.914	0.004	2,535	13,365
β1	-6,712	7,385	-0.909	0.366	-21,370	7,947
β2	5,467	15,824	0.346	0.730	-25,943	36,878
β3	-15,368	10,340	-1.486	0.140	-35,894	5,157

A predictive model is thus:

$$T = 7{,}950 - 6{,}712 * DOM + 5{,}467 * SPE - 15{,}368 * PRO \quad (10)$$

It thus appears that the presence of a dominant firm in an industrial cluster does not help the inventive activity of the cluster as measured by the total number of patent filings. Similarly, the greater the contribution of PROs to the inventive activity of a cluster the less the total productivity of the cluster is. Finally, increased specialization in an industrial cluster has a positive influence on the total number of patent filings.

While these results reveal distinct tendencies with respect to those characteristics of industrial clusters that do matter for innovation, there is an additional question of whether such tendencies are moderated by geography. To address this question, the analysis was repeated separately for the 38 clusters located in Europe; the 35 clusters located in North America; and the 22 top clusters located in Asia.

The analysis of the top manufacturing clusters in this study indicates that a higher degree of hierarchy appears to be a distinct advantage in terms of innovation. The presence of a dominant firm in an industrial cluster may be a hampering factor for innovation as measured by the total number of patent filings.

The results also indicate that while this statement is true for the whole set of industrial clusters, it is patently not true for European clusters. In fact, the presence of a dominant firm for these clusters appears to be a positive factor for innovation as measured by the total number of patent filings.

Clusters are assumed to confer competitive advantage due to the spatial and relational proximity of their members. It has been theorized that a distinct advantage of clusters has to do with the flow of information in business networks and the production, dissemination and absorption of knowledge [125,126]. The analysis of the top industrial clusters in this chapter indicates that cluster diversity tends to be an impediment and specialization an advantage in terms of innovation performance.

8.2. Policy interventions outputs and results

It can be hypothesized of course that policy interventions may have a delay in producing tangible results. Thus, this thesis proceeds further by exploring the concept of innovation as a *dynamic* process and examining the variable of time to study the evolution of the issues involved over the span of a decade, as well as the progress and accomplishment of the consequent policy interventions to resolve them.

As was articulated before, international governments and authorities have launched numerous innovation campaigns to inform about and induce innovation activity. These campaigns, aiming to encourage a wider focus on innovation, have been operating systematically for the better part of the last three decades. Their premise has remained quite consistent over the years based on the adage that governments can foster innovation in four basic ways: "by buying it, by reducing its risk, by collaborating on it, and by using standards or regulations to encourage it" [127]. The variety of policy tools for encouraging the development of innovation run the gamut from assisting with the cost of R&D (through direct government funding, and tax incentives), protecting IPRs, and supporting cooperative research ventures between universities and the private sector to, ultimately, being the lead consumer of it (defense, public health).

Most of these campaigns became recurrent and highly anticipated interventions targeting one or two obstacles of local significance, without further coordination within the context of a broad innovation policy. The effectiveness of these campaigns came recently under critical review that focused on the apparent failures to achieve stated targets [6,128]. In fact, there is very weak empirical evidence to support the effectiveness of innovative policies in numerous reviews of the issue [7,8].

In these reviews, policies such as government subsidies, tax deductions, soft loans, and public-private partnerships are explored as legitimate incentives for innovation that had limited effectiveness due to so-called "political" failures (stemming from conflicts between business entities, special interest groups and the public). Less attention, however, has been paid to failures that could possibly be attributed to the inherent structure of these campaigns. The role of the public sector in ensuring or undermining the effectiveness of innovation policy instruments is rarely considered. Indeed, a comprehensive text analysis of over 5,000 papers published in five leading innovation journals between 2010 and 2019, revealed the paucity of research on this issue [129].

The situation is exasperated by the fact that the *digital challenges* of the last decade have affected the field of innovation policy significantly. The determinants of innovation in the digital era include very broad interventions (such as initiatives to develop a highly skilled workforce or to provide reliable and speedy broadband internet) -in stark contrast to the narrow, targeted or industry-specific policies of the old [8,130]. Horizontal policies to create the human capital needed for innovation, to encourage the clustering of innovative activity and to enable knowledge spillovers have emerged as the key catalysts for an innovation-friendly environment in a specific region [131].

To resolve the question of whether promoting innovation succeeded, the large-scale data constituting three latest (completely published and an additional one recently released) CIS cover practically a decade during which numerous interventions in support of innovation were implemented in Europe at the regional, country and EU level [132].

Table 27. Demographics of CIS 2014, CIS 2016, CIS 2018 and CIS 2020.

Survey	CIS 2014	CIS 2016	CIS 2018	CIS 2020*
Periods covered:	Jan 2012 - Dec 2014	Jan 2014 - Dec 2016	Jan 2016 - Dec 2018	Jan 2018 - Dec 2020
Data released:	Jan 2017	Feb 2019	Jan 2021	Dec 2022
Countries surveyed:	34	35	31	29
Firms surveyed:	644,858	667,688	630,022	587,528
Non-innovative firms:	50%	48%	50%	48%

* *not completely released yet*

The demographics of these CIS surveys are summarized in Table 27. The percentage of non-innovative firms in the EU has remained constant across the years, hovering at 50%. For most countries, the percentage of non-innovative firms remained also fairly constant, with the notable exceptions of Portugal (where it actually *increased* significantly) and Italy and Estonia (where it decreased significantly) Appendix B

Validating the benchmarking example. Estonia of course reflects the views of only 3,000 firms (less than 0.5% of the total CIS sample) many of which are e-business in the digital sector.

As a matter of choice, among the reported EU members, Italy is one of a handful of countries for which data on the obstacles to innovation appear in all four surveys CIS 2014, CIS 2016, CIS 2018 and CIS 2020. (Inexplicably, data for Germany used as a benchmarking example appear in CIS 2014 and CIS 2016 but not in CIS 2018 and CIS 2020.)

The full descriptive statistics on all four samples from Italy are summarized in Table B1 in Appendix B

Validating the benchmarking example. Thus, Italy represents the concerns of a rich assortment of over 90,000 firms (about 15% of the total CIS sample) and is at the forefront of the EU agenda on innovation.

Since Italy is a prominent example of significant accomplishments in promoting innovation (with the number of its non-innovative firms measurably declined by almost a third with time), the focus of this study is on non-innovators, since the perceptions of non-innovative firms are more instructive in assessing innovation promotion campaigns.

Following the same procedure of Probit regression analysis and computation of predictive margins (as described in Chapter 4) the predicted importance of the innovation barriers as perceived by non-innovative firms in Italy was determined (Figure 18). The full results (predictive margins and their statistical significance) for all four samples are presented in Table B2, Table B3, Table B4 and Table B5 in Appendix B while for interpretive purposes the graphical representation is used in the thesis. (As was mentioned earlier CIS 2020 data are not used in the main analysis in this thesis but are presented in Appendix B.) The focus on several independent samples imposes another methodological note, as the varieties of the barriers reported in each CIS induce additional noise to the data, the study applies the taxonomy introduced and described in Chapter 2 and summarized in Table 13.

Thereby, Figure 18 depicts the predicted importance of the three classes of obstacles in CIS 2014, CIS 2016 and CIS 2018. For instance, finance, market, and knowledge obstacles were of high importance for 86%, 78% and 38% of the non-innovative firms respectively in CIS 2014. The same percentages became 73%, 76% and 57% in CIS 2016 and 21%, 19% and 13% in CIS 2018. (The dotted curve representing the percentage of non-innovative firms over the years is superimposed for reference purposes.)

Throughout this period, knowledge factors remained the least important barriers with finance barriers being the most important followed closely by market ones. (The primacy of demand and financial obstacles in hindering innovation has been observed in other parts of the world as well [133].) While the importance of the barriers related to finance and market has undergone similar changes (mostly decreasing over years at different rates), the importance of knowledge barriers increased by almost 20% from CIS 2014 to CIS 2016 and fell even more rapidly by 40% from CIS 2016 to CIS 2018. The inflection point of CIS 2016 for knowledge barriers is a peculiarity that warrants further investigation.

In order to increase the granularity of these findings, the firm layer characteristics (firm size and sector of operation) were introduced into the analysis, Thus, Figure 19 depicts the predicted importance of the barriers by small-, medium- and large-sized firms in CIS 2014, CIS 2016 and CIS 2018.

While the overall downward trend remains present, the inflection point in CIS 2016 for knowledge obstacles across all firm sizes is now evident as well for market obstacles perceived by MED firms and finance obstacles for LRG firms. The overall pattern seen in Figure 18 is influenced primarily by small firms. Indeed, small firms in Italy comprise for 85% of the total sample and account 80% of employment and 70% of value added in the country [134].

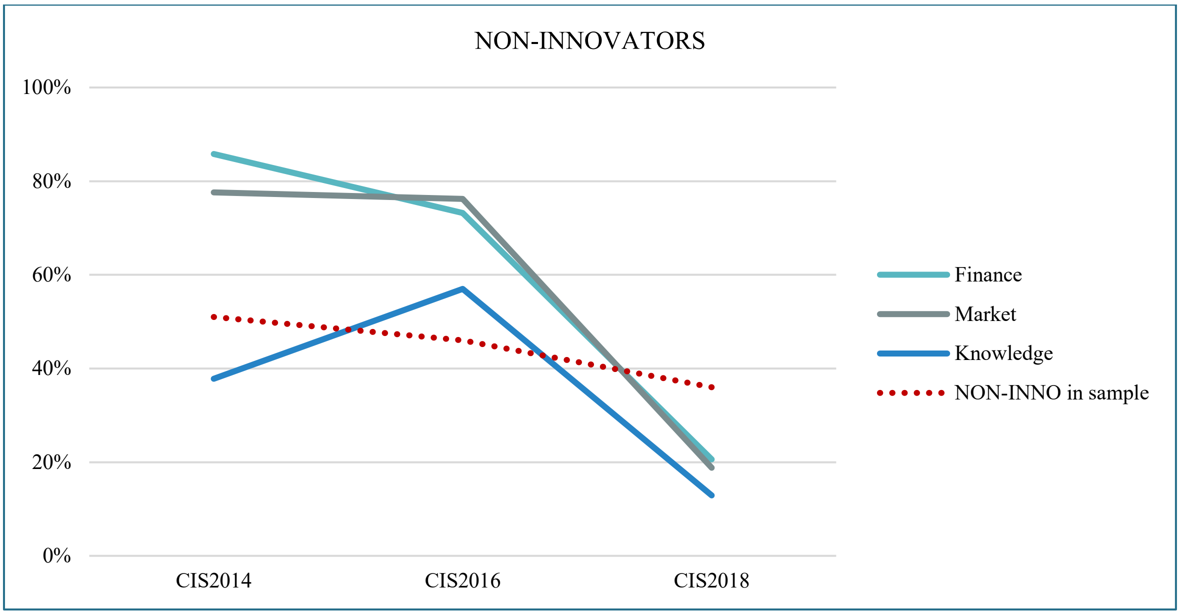


Figure 18. Predictive margins across time in Italy.

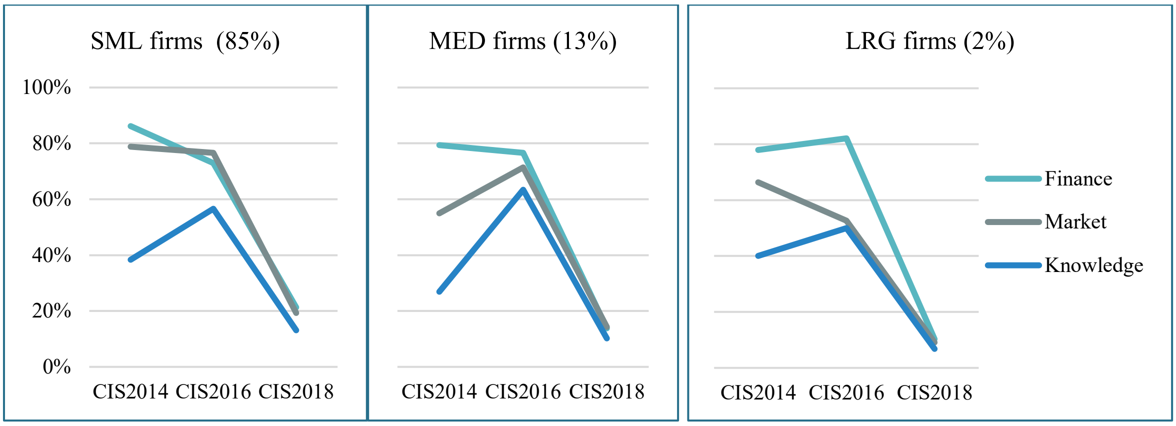


Figure 19. Predictive margins across time for size classes in Italy.

Similarly, Figure 20 depicts the predicted importance of the barriers by PROD and SERV firms in CIS 2014, CIS2 016 and CIS 2018.

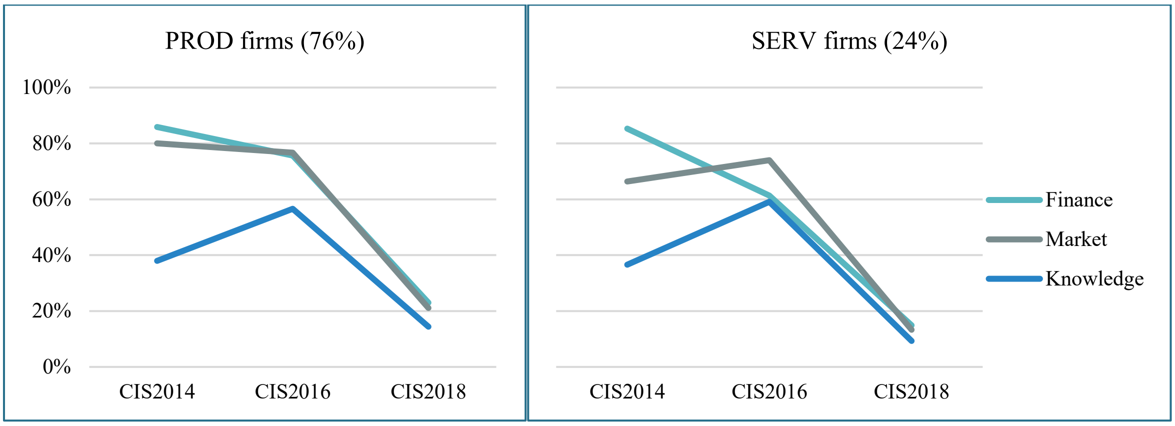


Figure 20. Predictive margins across time for sectors in Italy.

The overall downward trend remains present in this clustering as well, with the inflection point in CIS 2016 for knowledge obstacles across all firm sizes now evident as well for market obstacles as perceived by SERV firms. Once again, the predominance of PROD firms in the sample (and the real economy) is responsible for the overall pattern observed in Figure 18.

The results in this chapter demonstrate unequivocally that there have been measurable shifts in perceptions about innovation over the last decade in Europe. These shifts are present across all categories of obstacles (finance, market and knowledge) and indicate that these obstacles have become significantly less effective inhibitors of innovation. (The same downward trend from CIS 2016 to CIS 2018 is also observed across *innovative* firms; CIS 2014 did not survey the views of innovative companies. The results of the analysis for innovative firms are also included in Appendix B

Validating the benchmarking example for reference.) Apparently, the national and central EU campaigns in support of innovation and the public policies and interventions put forward have significantly reduced the threshold to overcome the “fear of innovation” [135].

Alas, while perceptions about barriers to innovation have been moderated this has not been reflected in an increase in the number of innovative enterprises. Indeed, this number has remained fairly constant over the decade in Europe (with Italy being the notable exception) against a background of continuously increasing overall investments in R&D (Figure 21) [136].

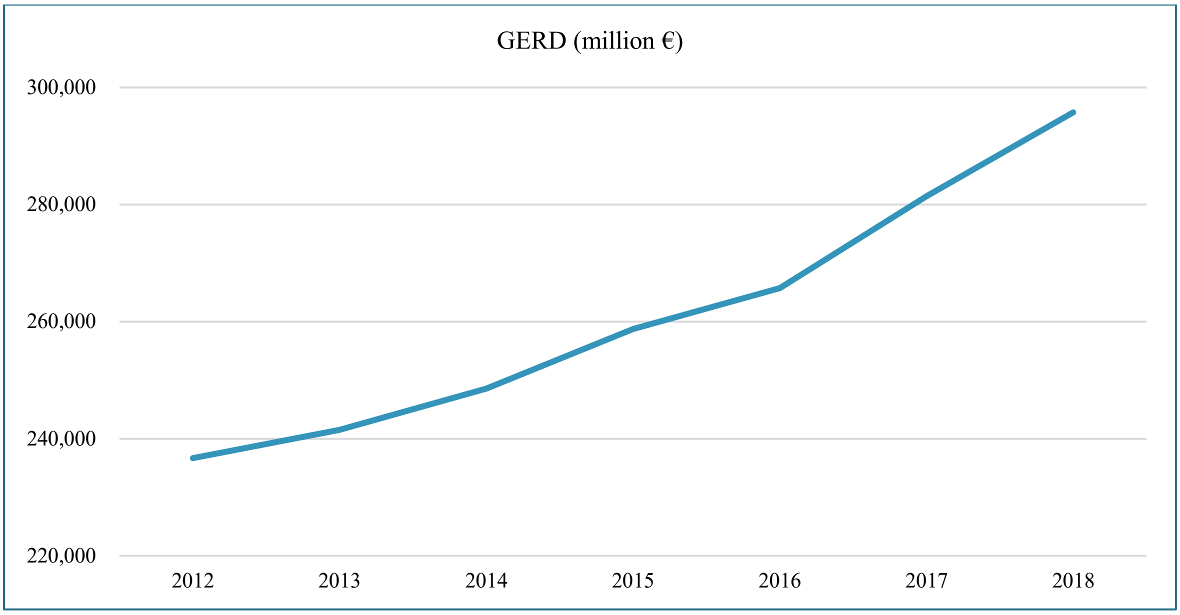


Figure 21. EU Gross Domestic Expenditure on R&D (GERD) excluding capital expenditures.

This exploratory study advances the thesis that Italy may be the key to understanding the extent to which innovation campaigns (or parts thereof) can transform shifts in perception into actual innovation action. The question is whether Italy's success in consistently increasing the number of its innovative enterprises over the last decade can be attributed to specific characteristics of its innovation ecosystem that can be identified and promoted.

Innovative firms develop competitive advantages for themselves and for their countries through knowledge exploitation and exploration and the creation of new technologies. Governments around the world constantly encourage their firms to compete in the digital era through policies that seek to promote and facilitate innovation. Except for the very few economies that possess the ability to capitalize on emerging technologies, most countries continue to experiment with their support of innovation with admittedly mixed results.

It has been demonstrated that promoting innovation over the last decade in Europe has led to a considerable shift in perceptions regarding obstacles to innovation so these obstacles have become significantly less effective inhibitors of innovation. Yet, neither promoting innovation nor continuously increasing investments in R&D has had any major effect in changing the number of innovative firms in Europe.

The distinct example of Italy, a country that has managed to increase its innovative firms consistently, indicates that its emphasis on improving skills and digital competencies along with financial and market incentives may be the key to success. In 2016 the Italian innovation ecosystem was at a turning point, with its historical weaknesses handicapping the technological progress of the country. The national plans of "Industria 4.0" and "la Buona Scuola" succeeded in changing the trend and enabling innovation measurably along with the "Gelmini Reform" [137,138]. Naturally, this emphasis at the policy level was effective because there was a mature and tightly controlled education system that could be coerced to adapt to the new challenges via government control of funding and curricula.

Indeed, new knowledge has emerged as a key commodity in the digital era and as a critical resource for innovation and entrepreneurship in Industry 4.0. The primacy of financial and market obstacles in hindering innovation remains undisputed the balance has shifted in favor of knowledge obstacles.

The determinants of innovation in the digital era include very broad interventions (such as initiatives to develop a highly skilled workforce or to increase gender diversity in R&D) -in stark contrast to the narrow, targeted or industry-specific policies of the old. Horizontal policies to create the human capital needed for innovation, encourage the clustering of innovative activity and enable knowledge spillovers have emerged as the key catalysts for an innovation-friendly environment in a region [93].

In this broader context, adherence to tried (and failed) models of innovation has led to political failures in innovation policy around the world. The evidence-based findings in this study and the example of Italy demonstrate succinctly the need for every country to adopt a harmonic model of innovation putting human capital at the forefront of the public innovation policy.

9. Conclusions and recommendations

The objective of this thesis, as set forth in the introduction, was to examine the innovation gap between a few leading countries, that possess the human and financial capital to create new knowledge and the market acumen to capitalize on it, and the rest of the world.

The issue is important because innovation is the driving force of economic growth, sustainable development, and social change. The uneven concentration of inventive activity increases the gap between developed and developing economies. The emergence of knowledge (both generation and utilization) as the critical component of the ongoing digital transformation of business activity, has exacerbated the situation over the last decade.

Innovation is an inherently difficult, financially risky, and mostly liable to fail process. Government attempts (at all levels) to encourage innovation through an array of fiscal subsidies and regulatory interventions have led to admittedly mixed results. Innovation policies around the world mostly imitate those of the leading countries without paying particular attention to the idiosyncrasies of the markets they purport to help. Such policies are based upon a generic understanding of the innovation process and are not sufficiently nuanced for the digital era.

Innovation of course starts at the firm level, with innovative firms developing competitive advantages for themselves and for their regions through knowledge exploration and exploitation and the creation of new technologies. Numerous business surveys and research studies in the past have been dedicated to identifying and assessing the importance of the obstacles that slow down and/or deter firms from innovating. Past research on innovation has sought to identify major correlates of innovation by assessing only one dimension of innovative behavior at each time. Treating the phenomenon of innovation as unidimensional does not sufficiently capture the richness of the construct of organizational innovation.

In this broad context, the objective of the thesis was to examine the process of innovation and to develop evidence-based insight into what inhibits innovation. The research presented in the previous chapters demonstrates that the process of innovation is decidedly multi-dimensional and introduces several layers of abstraction: the firm layer, the operational layer, the process layer, and the policy layer.

This novel dissection of the phenomenon of innovation, which is a distinct contribution of the thesis, was based on a range of multi-dimensional analytical approaches applied to publicly available datasets.

9.1. Contributions

The main objective of this thesis was to examine the determinants of innovation and develop evidence-based insight into what inhibits non-innovative firms from innovating and into what is important for innovative firms in their drive to excel.

The analysis was grounded on large-scale, publicly available data and brought forward new vantage points of the phenomenon of innovation. As the analysis of the determinants of innovation was structured around four distinct layers of abstraction, it is only fitting that the outcomes are presented along a similar multi-level schema.

Specifically, the achievements of the dissertation are articulated as follows:

- Outcomes at the *firm layer* are related to the way key characteristics of the profile of a firm (such as firm size, sector, and prior engagement in innovation activities) impact its innovativeness [18,28].
- Outcomes at the *operational layer* are related to the impact of factors in the operational environment within which innovation occurs, with emphasis on economic, market, cultural and gender diversity issues [31,94].
- Outcomes at the *process layer* are related to the impact of knowledge acquisition, elicitation, and management on the tangible innovation productivity of innovative firms [104,105,111].
- Outcomes at the *policy layer* are related to the perceived effect of innovation policies and interventions as assessed in hindsight with a special focus on the promotion of clustering activities and innovation hotspots [1,38].

It should be emphasized again that the four-tier architecture in Figure 2 does not presume a hierarchy or a dependency among the layers, other than the notion that policy interventions can, in principle, impact firm, operational and process issues. This four-tier architecture is put forward not as a functional model of innovation but rather as a construct aiming to organize distinct dimensions of innovation across a limited number of thematic axes.

The results of this evidence-based dissertation presented herein are instrumental in defining the specific facets of an effective, modern innovation policy, producing the desired performance outcomes in the context of limited resources for innovation. With this caveat in mind, the outcomes and corresponding recommendations of the dissertation are summarized below.

9.1.1. Firm layer

- All obstacles to innovation are perceived as far more important by non-innovative firms than by innovative ones. In this sense, fear of the "unknown" is a powerful deterrent to innovation. Revealed barriers on the other hand serve as a valuable learning experience for innovative firms and, while they may slow down, they will not stop innovation.
  - → *Policy recommendation: Entice non-innovative firms to engage in small innovative projects to familiarize themselves with the issues involved.*

- For innovative firms, all obstacles to innovation are perceived as increasingly less important as the size of the firm increases. This is not true for non-innovative firms, where the perceived importance -especially of financial obstacles- increases considerably with the size of the firm.
  - → *Policy recommendation: Entice medium and especially large non-innovative firms to engage in innovation by providing fiscal subsidies to reduce their perception of risk.*

- The importance of almost every obstacle is slightly higher for firms engaged in production activities as opposed to firms that operate in the service sector. Financial barriers are marginally more important for service firms that do innovate, but not for non-innovative ones.
  - → *Policy recommendation: Entice innovative service firms to intensify their innovation by providing the (relatively small) fiscal incentives needed to facilitate the process.*

9.1.2. Operational layer

- The argument of an alleged cultural divide being the cause of asymmetries in innovation performance is challenged by the data. It is difficult to discern an East-West divide in the European context, with firm-level characteristics appearing to be broadly uniform and largely responsible for country-specific differences.
  - → *Policy recommendation: As differences in perception are mostly due to the diffusion of firm-level factors, regional policies that discriminate on the basis of outdated social norms are irrelevant today.*

- The argument that the level of development of a country in which a firm operates impacts its innovation performance is supported by the data. Innovation performance has emerged as a key factor distinguishing the less-developed “Global South” countries from the more developed “Global North” ones.
  - → *Policy recommendation: Initiatives to encourage and support innovation in less developed countries should be prioritized within the 2030 Agenda for Sustainable Development of the United Nations.*

- For Kazakhstan, a country in the Global South, a gender-balanced scientific workforce has emerged as an important factor for innovation. The effect was more pronounced in terms of access to digital technologies and digital upskilling. Minor variations across firm sizes and sectors did not disguise the importance of alleviating gender disparity in the teams implementing and supporting innovation in the country.
  - → *Policy recommendation: Initiatives to encourage greater inclusion of women in the digital economy can have tangible economic and social benefit.*

9.1.3. Process layer

- While several knowledge sources are articulated in the innovation literature, innovative firms still create or procure knowledge primarily from within their enterprise group and from their clients or customers. This observation is further amplified by the fact that the lion’s share of innovation expenditures is devoted to internal R&D with very limited resources targeting external contract research or outright acquisition of knowledge from third parties. This observation is true across firm sizes and sectors and reflects the efficiency of information flows within tight-knit organizations.
  - → *Policy recommendation: Initiatives to encourage knowledge sharing and collaboration between firms by providing funding for joint research projects, organizing networking events, and promoting industry partnerships.*

- Large manufacturing firms remain the dominant players in the invention, protection, and commercialization of new technologies. The majority of SMEs remain technology followers and, when they need to protect their inventions, they prefer trade secrets as they cannot afford the pressure of high litigation risk associated with patenting.

→ *Policy recommendation: Entice small and medium manufacturing firms to engage more in protecting their inventions by providing fiscal subsidies, tax breaks and legal support.*

- A gender-balanced scientific workforce has also emerged as an important factor for innovation in the industrial clusters. The contribution of women inventors tends to directly impact tangible innovation performance as measured by patent applications.

  → *Policy recommendation: Initiatives to encourage greater inclusion of women inventors in the industrial clusters and innovation hotspots by providing funding for women-led initiatives and start-ups.*

9.1.4. Policy layer

- Business clusters confer competitive advantage to their members as they facilitate the flow of information the production, dissemination, and absorption of knowledge. Within clusters, specialization confers a distinct advantage, and the presence of a dominant firm is a positive factor for innovation as measured by the total number of patent filings.

  → *Policy recommendation: Cluster policies should focus on the support of business networks with a distinct thematic axis, preferably around an established dominant firm.*

- Innovation campaigns with a targeted emphasis on improving skills and digital competencies in the workforce have been effective in increasing innovation in an economy.

  → *Policy recommendation: Entice the policymakers to implement more nuanced campaigns coupling financial and market incentives with the necessary digital upskilling of the workforce.*

9.2. Limitations and future work

Admittedly, the studies from which these outcomes emerged are limited by the paucity of reliable and consistent data on innovation worldwide. Indeed, the exploratory studies in this thesis set the stage for future research and pose key questions on the efficacy of innovation indicators collected and the metrics employed worldwide.

Several of the outcomes of this dissertation are grounded on the analysis of extensive datasets transcending several countries, and thus have increased significance. A few outcomes are based on single-country datasets due to deficiencies in the format or structure of even large innovation surveys.

With this caveat in mind, the methodological rules for data agglomeration, pre-processing and analysis presented in this thesis may be applied to the future study of the cultural divide on the extended sample (accumulating the CIS data from additional countries) and to the extended longitudinal study of the characteristics and outcomes of policy interventions (accumulating the CIS data from subsequent releases).

In a word, the key outcomes of the thesis, and several other relevant corollaries that emerged, can form the basis of targeted studies that will address the determinants of innovation that the present dissertation has revealed. The analysis herein has revealed the need for primary data resourced based on the exploratory studies of the dissertation.

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Appendix A

Benchmarking example of Germany

The analysis at the firm layer is grounded in the benchmarking example of innovation-leader Germany.

First, descriptive statistics of firms that participated in the survey from Germany for all four latest CIS releases are summarized in Table A1.

DE	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	72,815	63%	75,855	60%	76,824	62%	84,265	63%
MED	22,522	78%	24,304	79%	25,358	81%	27,130	81%
LRG	5,650	94%	6,025	91%	6,678	88%	7,143	92%
Total Size class	**100,987**	**68%**	**106,184**	**66%**	**108,860**	**68%**	**118,538**	**69%**
Sector:								
PROD	67,139	71%	68,619	69%	68,985	71%	73,667	73%
SERV	33,848	61%	37,565	60%	39,875	64%	44,871	63%
Total Sector	**100,987**	**68%**	**106,184**	**66%**	**108,860**	**68%**	**118,538**	**69%**

Table A1. Descriptive statistics of the sample DE.

Constrained by the data available on the obstacles to innovation (data for Germany not released in CIS 2018 and later) the focus is on the sample of Germany from CIS 2016.

As the reporting of the data on obstacles to innovation occurs in binary nature, thus, reporting the definite opinions of the firms on the importance of the obstacles, Table A2 summarizes the number of votes given for "High" and "None" importance values.

DE	**LFIN_IN**		**LFIN_EXT**		**H_COST**		**L_SUBS**		**U_DMND**		**H_COMP**		**L_EMPL**		**L_PRTN**	
2016	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE
Innovative firms (INNO)																
Size class:																
SML	7,163	17,332	5,071	19,581	10,863	11,809	6,027	18,763	4,547	16,268	4,178	16,879	8,200	12,668	2,648	19,780
MED	1,734	8,084	1,045	9,650	3,840	5,320	1,684	8,992	1,087	7,455	1,240	8,526	1,991	5,465	580	8,764
LRG	371	2,464	150	3,192	804	1,227	359	2,903	455	2,028	232	2,207	629	1,387	86	2,558
Sector:																
PROD	5,808	18,303	4,037	21,068	10,727	12,037	5,378	19,853	4,893	16,918	4,447	17,573	7,880	12,788	2,535	20,926
SERV	3,460	9,577	2,229	11,355	4,780	6,319	2,692	10,805	1,196	8,833	1,203	10,039	2,940	6,732	779	10,176
Total	**9,268**	**27,880**	**6,266**	**32,423**	**15,507**	**18,356**	**8,070**	**30,658**	**6,089**	**25,751**	**5,650**	**27,612**	**10,820**	**19,520**	**3,314**	**31,102**
Total	37,148		38,689		33,863		38,728		31,840		33,262		30,340		34,416	
69,973	(53%)		(55%)		(48%)		(55%)		(46%)		(48%)		(43%)		(49%)	

DE	**LFIN_IN**		**LFIN_EXT**		**H_COST**		**L_SUBS**		**U_DMND**		**H_COMP**		**L_EMPL**		**L_PRTN**	
2016	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE	HIGH	NONE
Non-innovative firms (NON-INNO)																
Size class:																
SML	2,501	5,590	1,806	6,249	4,507	3,404	2,170	5,410	1,515	5,518	3,102	4,750	2,995	3,085	1,427	5,683
MED	356	710	317	868	488	338	332	762	229	704	307	836	350	418	265	826
LRG	58	71	52	72	74	13	18	96	16	113	60	72	59	57	9	95
Sector:																
PROD	2,011	3,458	1,492	3,840	3,430	1,501	1,541	3,476	1,179	3,217	2,105	3,294	2,051	1,849	1,131	3,354
SERV	904	2,913	683	3,349	1,639	2,254	979	2,792	581	3,118	1,364	2,364	1,353	1,711	570	3,250
Total	**2,915**	**6,371**	**2,175**	**7,189**	**5,069**	**3,755**	**2,520**	**6,268**	**1,760**	**6,335**	**3,469**	**5,658**	**3,404**	**3,560**	**1,701**	**6,604**
Total	9,286		9,364		8,824		8,788		8,095		9,127		6,964		8,305	
69,973	(26%)		(26%)		(24%)		(24%)		(22%)		(25%)		(19%)		(23%)	
All firms (INNO and NON-INNO)																
Total	46,434		48,053		42,687		47,516		39,935		42,389		37,304		42,721	
106,184	(44%)		(45%)		(40%)		(45%)		(38%)		(40%)		(35%)		(40%)	

Table A2. Firms expressing a clear opinion on obstacles: DE 2016 across size classes, sectors and innovativeness.

Next, the computed predicted margins (and their statistical significance) obtained from the econometric model described in Chapter 4 are reported for Germany CIS 2016 sample across several levels of granularization (so-called exploratory cases) on the example of INNO firms.

For instance, the results for Case 1, where the dependent variables are regressed across size class and sector of the firm independently, are presented in Table A3. This thesis proceeds with this approach selected as the main scheme.

CASE 1: Size class *or* sector (selected for this study):

DE 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.292	0.206	0.479	0.243	0.218	0.197	0.394	0.118
	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]
2 (MED)	0.177	0.098	0.419	0.158	0.128	0.129	0.265	0.063
	[0.004***]	[0.003***]	[0.005***]	[0.004***]	[0.004***]	[0.003***]	[0.005***]	[0.003***]
3 (LRG)	0.131	0.045	0.395	0.109	0.184	0.094	0.310	0.032
	[0.006***]	[0.004***]	[0.011***]	[0.005***]	[0.008***]	[0.006***]	[0.010***]	[0.003***]
Sector:								
1 (PROD)	0.241	0.161	0.472	0.215	0.224	0.201	0.383	0.108
	[0.003***]	[0.002***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]
2 (SERV)	0.264	0.163	0.430	0.197	0.120	0.108	0.301	0.072
	[0.004***]	[0.003***]	[0.005***]	[0.003***]	[0.003***]	[0.003***]	[0.005***]	[0.002***]
N	37,148	38,689	33,863	38,728	31,840	33,262	30,340	34,416

DE 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.311	0.226	0.570	0.287	0.219	0.395	0.494	0.204
	[0.005***]	[0.005***]	[0.005***]	[0.005***]	[0.005***]	[0.006***]	[0.006***]	[0.005***]
2 (MED)	0.319	0.255	0.585	0.298	0.219	0.268	0.446	0.221
	[0.014***]	[0.012***]	[0.016***]	[0.014***]	[0.013***]	[0.013***]	[0.018***]	[0.012***]
3 (LRG)	0.468	0.436	0.840	0.162	0.127	0.456	0.516	0.095
	[0.043***]	[0.044***]	[0.038***]	[0.035***]	[0.030***]	[0.043***]	[0.046***]	[0.029***]
Sector:								
1 (PROD)	0.368	0.280	0.695	0.306	0.268	0.390	0.527	0.251
	[0.007***]	[0.006***]	[0.007***]	[0.007***]	[0.007***]	[0.007***]	[0.008***]	[0.007***]
2 (SERV)	0.236	0.169	0.421	0.260	0.157	0.366	0.440	0.150
	[0.007***]	[0.006***]	[0.008***]	[0.007***]	[0.006***]	[0.008***]	[0.009***]	[0.006***]
N	9,286	9,364	8,824	8,788	8,095	9,127	6,964	8,305

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table A3. Predictive margins on obstacles to innovation: DE 2016, INNO and NON-INNO firms across size classes or sectors.

Next, the results of the exploratory analysis with inclusion of *interaction effects* [80], i.e. the case where the dependent variables are regressed *both* across the size class and sector, are presented in Table A4.

CASE 2: Size class *and* sector:

DE 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class with Sector = 1 (PROD):								
1 (SML)	0.277	0.208	0.484	0.242	0.260	0.234	0.411	0.141
	[0.004***]	[0.003***]	[0.004***]	[0.003***]	[0.004***]	[0.004***]	[0.004***]	[0.003***]
2 (MED)	0.182	0.090	0.460	0.174	0.135	0.147	0.322	0.050
	[0.005***]	[0.003***]	[0.006***]	[0.005***]	[0.004***]	[0.004***]	[0.006***]	[0.003***]
3 (LRG)	0.136	0.045	0.383	0.131	0.237	0.135	0.310	0.033
	[0.008***]	[0.004***]	[0.013***]	[0.007***]	[0.010***]	[0.009***]	[0.012***]	[0.004***]
Size class with Sector = 2 (SERV):								
1 (SML)	0.321	0.201	0.469	0.245	0.128	0.126	0.357	0.068
	[0.005***]	[0.004***]	[0.006***]	[0.005***]	[0.004***]	[0.004***]	[0.006***]	[0.003***]
2 (MED)	0.166	0.111	0.337	0.126	0.110	0.092	0.142	0.088
	[0.006***]	[0.005***]	[0.009***]	[0.005***]	[0.006***]	[0.004***]	[0.007***]	[0.005***]
3 (LRG)	0.120	0.044	0.428	0.062	0.075	0.019	0.318	0.032
	[0.011***]	[0.006***]	[0.020***]	[0.008***]	[0.009***]	[0.005***]	[0.019***]	[0.006***]
N	37,148	38,689	33,863	38,728	31,840	33,262	30,340	34,416

DE 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class with Sector = 1 (PROD):								
1 (SML)	0.365	0.273	0.692	0.307	0.270	0.405	0.532	0.250
	[0.007***]	[0.006***]	[0.007***]	[0.007***]	[0.007***]	[0.007***]	[0.008***]	[0.007***]
2 (MED)	0.373	0.305	0.706	0.319	0.270	0.277	0.484	0.270
	[0.015***]	[0.014***]	[0.016***]	[0.015***]	[0.015***]	[0.014***]	[0.018***]	[0.014***]
3 (LRG)	0.530	0.499	0.915	0.176	0.163	0.466	0.554	0.122
	[0.045***]	[0.046***]	[0.026***]	[0.037***]	[0.036***]	[0.044***]	[0.046***]	[0.036***]
Size class with Sector = 2 (SERV):								
1 (SML)	0.234	0.164	0.417	0.261	0.158	0.380	0.445	0.150
	[0.007***]	[0.006***]	[0.008***]	[0.007***]	[0.006***]	[0.008***]	[0.009***]	[0.006***]
2 (MED)	0.240	0.188	0.432	0.272	0.159	0.256	0.398	0.164
	[0.014***]	[0.012***]	[0.019***]	[0.015***]	[0.013***]	[0.014***]	[0.019***]	[0.012***]
3 (LRG)	0.380	0.353	0.745	0.143	0.085	0.441	0.467	0.063
	[0.043***]	[0.043***]	[0.053***]	[0.032***]	[0.023***]	[0.044***]	[0.047***]	[0.022***]
N	9,286	9,364	8,824	8,788	8,095	9,127	6,964	8,305

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table A4. Predictive margins on obstacles to innovation: DE 2016, INNO and NON-INNO firms across size classes and sectors.

The methodological rules described in Chapter 4 were then applied in another context – applying, registering and using the different form of forms of IPRs the manufacturing firms of different sizes and innovativeness in Germany (CIS 2016). Table A5 reports the computed predicted probabilities of the firms applying, registering or using certain IPRs.

DE 2016	Any IPRs	Patent	Trademark	Utility model	Industrial design	Trade secret	Copyright
Innovative firms (INNO), 44,447 observations							
1 (SML)	0.577	0.182	0.148	0.139	0.077	0.444	0.064
	[0.003] ***	[0.002] ***	[0.002] ***	[0.002] ***	[0.002] ***	[0.003] ***	[0.001] ***
2 (MED)	0.749	0.353	0.245	0.241	0.106	0.600	0.098
	[0.004] ***	[0.004] ***	[0.004] ***	[0.004] ***	[0.003] ***	[0.004] ***	[0.003] ***
3 (LRG)	0.904	0.623	0.444	0.384	0.176	0.734	0.193
	[0.005] ***	[0.008] ***	[0.008] ***	[0.008] ***	[0.006] ***	[0.007] ***	[0.006] ***
Non-innovative firms (NON-INNO), 18,962 observations							
1 (SML)	0.190	0.054	0.076	0.049	0.043	0.141	0.047
	[0.003] ***	[0.002] ***	[0.002] ***	[0.002] ***	[0.002] ***	[0.003] ***	[0.002] ***
2 (MED)	0.397	0.148	0.162	0.142	0.140	0.284	0.096
	[0.009] ***	[0.006] ***	[0.007] ***	[0.006] ***	[0.006] ***	[0.008] ***	[0.005] ***
3 (LRG)	0.710	0.124	0.131	0.120	0.247	0.360	0.018
	[0.027] ***	[0.020] ***	[0.020] ***	[0.019] ***	[0.026] ***	[0.029] ***	[0.008] **

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table A5. Predictive margins on IPRs: DE 2016, manufacturing firms across size classes and innovativeness.

The CIS data on Germany in 2016 were utilized further addressing the knowledge acquisition and management processes. The tables summarize the number of the assessment of the innovative firms (in absolute and relative values) of the importance of various knowledge sources (Table A6 and Table A7) and the amounts of expenditures on innovation (Table A8 and Table A9) across the size classes and sectors.

	GROUP	SUPPL	PRIVT	PUBLC	COMPT	CONSLT	UNIVS	GOVRN	FAIRS	PRINT	ASSOC	Total
Size class:												
SML	20,452	3,228	12,123	2,545	4,712	1,102	2,001	771	4,611	2,459	1,260	55,264
MED	9,890	1,167	5,331	1,035	2,431	782	1,035	426	2,091	999	922	26,109
LRG	3,451	407	2,111	421	1,214	317	552	207	766	451	391	10,288
Total	**33,793**	**4,802**	**19,565**	**4,001**	**8,357**	**2,201**	**3,588**	**1,404**	**7,468**	**3,909**	**2,573**	**91,661**
Sector:												
MFG	21,558	3,465	13,964	2,154	5,518	1,125	2,392	908	5,799	2,452	1189	60,524
INF	6,844	592	3,229	1,337	1,370	464	948	305	1,076	1,074	280	17,519
Total	**4,057**	**17,193**	**3,491**	**6,888**	**1,589**	**3,340**	**1,213**	**6,875**	**3,526**	**1,469**	**78,043**	**4,057**

Table A6. Characterization of knowledge sources for innovation as highly important (votes).

	GROUP	SUPPL	PRIVT	PUBLC	COMPT	CONSLT	UNIVS	GOVRN	FAIRS	PRINT	ASSOC	Total
Size class:												
SML	37%	6%	22%	5%	9%	2%	4%	1%	8%	4%	2%	100%
MED	38%	5%	20%	4%	9%	3%	4%	2%	8%	4%	4%	100%
LRG	34%	4%	21%	4%	12%	3%	5%	2%	7%	4%	4%	100%
Total	**37%**	**6%**	**21%**	**4%**	**9%**	**2%**	**4%**	**2%**	**8%**	**4%**	**3%**	**100%**
Sector:												
MFG	36%	6%	23%	4%	9%	2%	4%	2%	10%	4%	2%	100%
INF	39%	3%	18%	8%	8%	3%	5%	2%	6%	6%	2%	100%
Total	**36%**	**5%**	**22%**	**4%**	**9%**	**2%**	**4%**	**2%**	**9%**	**5%**	**2%**	**100%**

Table A7. Characterization of knowledge sources for innovation as highly important (% of votes).

	Internal R&D	External R&D	Acquisition of external knowledge	Total
Size class:				
SML	2,905	413	221	3,539
MED	5,207	750	365	6,322
LRG	65,528	13,549	1,873	80,950
Total	**73,640**	**14,712**	**2,459**	**90,811**
Sector:				
MFG	63,600	13,266	1,211	78,077
INF	4,040	656	713	6,273
Total	**67,640**	**13,922**	**1,924**	**84,350**

Table A8. Innovation expenditures (million €).

	Internal R&D	External R&D	Acquisition of external knowledge	Total
Size class:				
SML	82%	12%	6%	100%
MED	82%	12%	6%	100%
LRG	81%	17%	2%	100%
Total	**82%**	**13%**	**5%**	**100%**
Sector:				
MFG	81%	17%	2%	100%
INF	78%	10%	11%	100%
Total	**80%**	**17%**	**2%**	**100%**

Table A9. Innovation expenditures (%).

Appendix B

Validating the benchmarking example

Temporal extension of the study

First, descriptive statistics of firms that participated in the survey from Italy are summarized (covering all four CIS releases, thus the 2012-2022 period).

IT	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	78,102	45%	80,034	51%	81,924	61%	80,289	53%
MED	12,060	69%	12,333	71%	12,961	77%	13,289	71%
LRG	2,045	85%	2,083	85%	2,198	85%	2,306	81%
Total Size class	**92,207**	**49%**	**94,450**	**54%**	**97,083**	**64%**	**95,884**	**56%**
Sector:								
PROD	71,355	50%	71,978	57%	73,491	66%	72,048	58%
SERV	20,852	43%	22,472	45%	23,592	57%	23,836	48%
Total Sector	**92,207**	**49%**	**94,450**	**54%**	**97,083**	**64%**	**95,884**	**56%**

Table B1. Descriptive statistics of the sample IT.

Italy 2014

Next, the predictive margins (and their statistical significance) across the selected CIS releases were computed. (NON-INNO firms only for CIS 2014.)

IT 2014	LFIN_IN	LFIN_EXT	L_SUBS	U_DMND	L_EMPL	L_PRTN
			Non-innovative firms (NON-INNO)			
Size class:						
1 (SML)	0.904	0.804	0.877	0.703	0.455	0.327
	[0.004***]	[0.006***]	[0.004***]	[0.004***]	[0.008***]	[0.007***]
2 (MED)	0.855	0.730	0.695	0.679	0.349	0.195
	[0.020***]	[0.025***]	[0.025***]	[0.012***]	[0.034***]	[0.026***]
3 (LRG)	0.969	0.602	0.759	0.593	0.582	0.245
	[0.031***]	[0.086***]	[0.074***]	[0.053***]	[0.111***]	[0.094***]
Sector:						
1 (PROD)	0.906	0.795	0.894	0.705	0.490	0.295
	[0.004***]	[0.007***]	[0.004***]	[0.004***]	[0.009***]	[0.007***]
2 (SERV)	0.889	0.808	0.740	0.691	0.275	0.450
	[0.009***]	[0.012***]	[0.013***]	[0.006***]	[0.017***]	[0.018***]
N	6,550	4,920	5,853	17,231	3,631	4,578

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B2. Predictive margins: IT 2014, size classes or sectors.

Italy 2016

IT 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.595	0.509	0.391	0.343	0.728	0.759	0.576	0.177
	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.003***]
2 (MED)	0.363	0.296	0.306	0.321	0.639	0.546	0.367	0.146
	[0.009***]	[0.008***]	[0.011***]	[0.009***]	[0.009***]	[0.012***]	[0.008***]	[0.007***]
3 (LRG)	0.370	0.237	0.213	0.238	0.595	0.493	0.294	0.083
	[0.020***]	[0.016***]	[0.020***]	[0.019***]	[0.020***]	[0.028***]	[0.018***]	[0.012***]
Sector:								
1 (PROD)	0.559	0.475	0.411	0.364	0.716	0.753	0.551	0.177
	[0.004***]	[0.004***]	[0.005***]	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.003***]
2 (SERV)	0.521	0.427	0.230	0.225	0.687	0.606	0.479	0.139
	[0.009***]	[0.008***]	[0.008***]	[0.007***]	[0.007***]	[0.009***]	[0.007***]	[0.006***]
N	18,075	20,017	14,086	16,600	19,207	14,954	20,968	18,514

IT 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.884	0.673	0.582	0.574	0.800	0.917	0.731	0.400
	[0.004***]	[0.007***]	[0.007***]	[0.006***]	[0.005***]	[0.003***]	[0.006***]	[0.006***]
2 (MED)	0.892	0.794	0.483	0.565	0.584	0.913	0.806	0.400
	[0.013***]	[0.018***]	[0.030***]	[0.027***]	[0.025***]	[0.013***]	[0.020***]	[0.029***]
3 (LRG)	0.962	0.810	0.463	0.129	0.393	0.907	0.772	0.155
	[0.027***]	[0.073***]	[0.130***]	[0.082]	[0.086***]	[0.062***]	[0.088***]	[0.083*]
Sector:								
1 (PROD)	0.909	0.699	0.610	0.592	0.774	0.914	0.728	0.397
	[0.004***]	[0.007***]	[0.007***]	[0.007***]	[0.005***]	[0.004***]	[0.006***]	[0.006***]
2 (SERV)	0.767	0.623	0.397	0.480	0.843	0.936	0.777	0.410
	[0.012***]	[0.015***]	[0.017***]	[0.015***]	[0.011***]	[0.008***]	[0.013***]	[0.016***]
N	7,501	5,651	5,625	6,512	6,803	7,002	6,854	6,673

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B3. Predictive margins: IT 2016, size classes or sectors.

Italy 2018

IT 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.314	0.193	0.389	0.215	0.339	0.473	0.238	0.104	0.095	0.169
	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]
2 (MED)	0.153	0.106	0.213	0.150	0.263	0.407	0.169	0.063	0.055	0.192
	[0.005***]	[0.004***]	[0.007***]	[0.005***]	[0.007***]	[0.008***]	[0.006***]	[0.004***]	[0.003***]	[0.006***]
3 (LRG)	0.107	0.070	0.156	0.090	0.234	0.331	0.097	0.041	0.030	0.195
	[0.011***]	[0.008***]	[0.014***]	[0.009***]	[0.016***]	[0.017***]	[0.011***]	[0.007***]	[0.006***]	[0.014***]
Sector:										
1 (PROD)	0.279	0.172	0.380	0.197	0.368	0.488	0.248	0.104	0.095	0.173
	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]
2 (SERV)	0.287	0.184	0.277	0.216	0.184	0.365	0.153	0.069	0.064	0.174
	[0.006***]	[0.005***]	[0.006***]	[0.005***]	[0.005***]	[0.006***]	[0.005***]	[0.003***]	[0.003***]	[0.005***]
N	28,749	32,086	24,626	35,332	27,511	27,102	25,334	31,353	29,980	29,405

IT 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.224	0.155	0.263	0.151	0.180	0.249	0.145	0.085	0.082	0.216
	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]	[0.003***]
2 (MED)	0.156	0.103	0.159	0.089	0.131	0.214	0.107	0.063	0.055	0.184
	[0.009***]	[0.007***]	[0.009***]	[0.006***]	[0.008***]	[0.010***]	[0.008***]	[0.006***]	[0.005***]	[0.009***]
3 (LRG)	0.135	0.051	0.125	0.052	0.099	0.126	0.060	0.026	0.026	0.162
	[0.024***]	[0.015***]	[0.024***]	[0.015***]	[0.022***]	[0.023***]	[0.018***]	[0.011**]	[0.011**]	[0.026***]
Sector:										
1 (PROD)	0.237	0.164	0.291	0.156	0.210	0.270	0.168	0.094	0.090	0.226
	[0.003***]	[0.003***]	[0.004***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.003***]
2 (SERV)	0.168	0.116	0.165	0.120	0.096	0.186	0.083	0.057	0.054	0.180
	[0.005***]	[0.004***]	[0.005***]	[0.004***]	[0.004***]	[0.005***]	[0.003***]	[0.003***]	[0.003***]	[0.005***]
N	22,466	23,524	22,669	25,028	23,430	23,488	21,882	24,072	23,158	23,349

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B4. Predictive margins: IT 2018, size classes or sectors.

Italy 2020

IT 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.246	0.170	0.357	0.181	0.290	0.312	0.261	0.107	0.109	0.234
	[0.003***]	[0.003***]	[0.004***]	[0.003***]	[0.003***]	[0.004***]	[0.004***]	[0.002***]	[0.002***]	[0.003***]
2 (MED)	0.098	0.067	0.160	0.107	0.210	0.257	0.157	0.049	0.054	0.190
	[0.004***]	[0.003***]	[0.006***]	[0.004***]	[0.007***]	[0.007***]	[0.006***]	[0.003***]	[0.003***]	[0.006***]
3 (LRG)	0.082	0.051	0.111	0.071	0.203	0.251	0.077	0.027	0.025	0.141
	[0.009***]	[0.007***]	[0.012***]	[0.008***]	[0.016***]	[0.016***]	[0.010***]	[0.005***]	[0.005***]	[0.013***]
Sector:										
1 (PROD)	0.213	0.150	0.338	0.159	0.297	0.320	0.247	0.100	0.095	0.233
	[0.003***]	[0.002***]	[0.004***]	[0.003***]	[0.004***]	[0.004***]	[0.004***]	[0.002***]	[0.002***]	[0.003***]
2 (SERV)	0.202	0.125	0.241	0.175	0.204	0.237	0.206	0.071	0.099	0.195
	[0.005***]	[0.004***]	[0.006***]	[0.005***]	[0.005***]	[0.006***]	[0.006***]	[0.003***]	[0.004***]	[0.005***]
N	23,436	26,875	20,570	26,904	21,307	19,952	19,523	24,474	23,092	24,068

IT 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.197	0.127	0.251	0.136	0.154	0.192	0.170	0.089	0.072	0.176
	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.002***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]
2 (MED)	0.078	0.048	0.093	0.054	0.074	0.056	0.049	0.025	0.027	0.161
	[0.005***]	[0.004***]	[0.006***]	[0.004***]	[0.005***]	[0.005***]	[0.005***]	[0.003***]	[0.003***]	[0.007***]
3 (LRG)	0.042	0.046	0.068	0.051	0.053	0.042	0.050	0.017	0.011	0.129
	[0.012***]	[0.012***]	[0.015***]	[0.012***]	[0.013***]	[0.011***]	[0.014***]	[0.008**]	[0.006*]	[0.020***]
Sector:										
1 (PROD)	0.197	0.132	0.253	0.133	0.159	0.173	0.174	0.089	0.073	0.187
	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.003***]
2 (SERV)	0.148	0.088	0.191	0.113	0.114	0.185	0.119	0.066	0.053	0.145
	[0.004***]	[0.003***]	[0.005***]	[0.003***]	[0.004***]	[0.004***]	[0.004***]	[0.003***]	[0.002***]	[0.004***]
N	25,326	26,213	25,376	27,027	25,449	24,739	23,845	27,586	26,310	27,041

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B5. Predictive margins: IT 2020, size classes or sectors.

Geographic extension of the study

Following the analysis of the predicted importance of the obstacles to innovation determined for CIS 2016 in Germany, the same analysis was conducted in other countries.

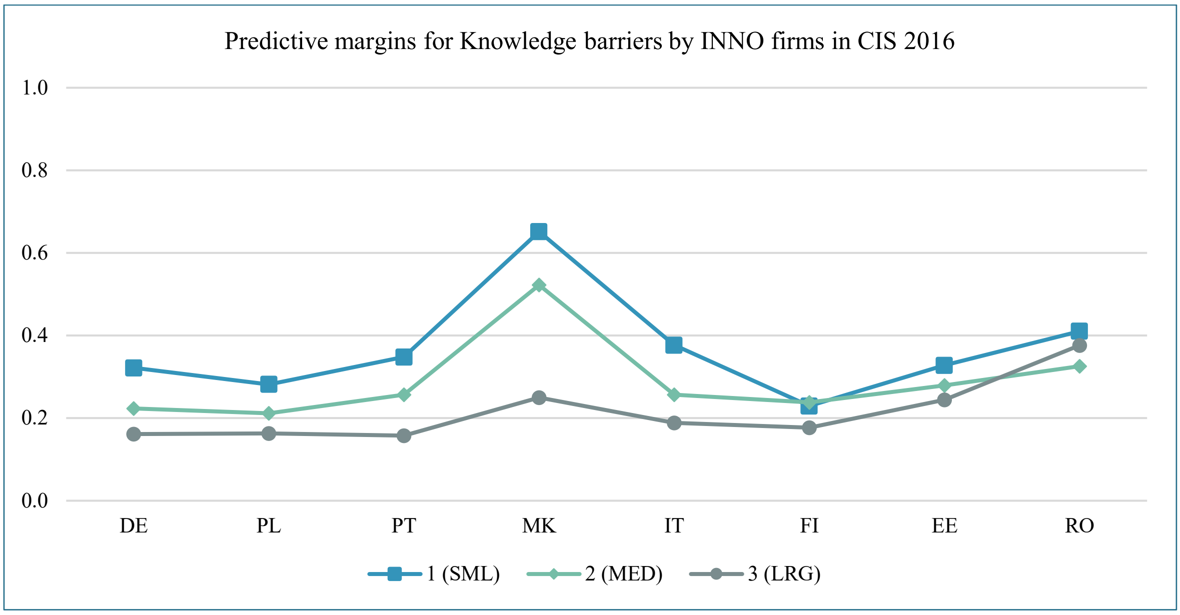

Figure B1. Predictive margins: Innovative firms assessing Knowledge barriers as highly important across size classes in different countries.

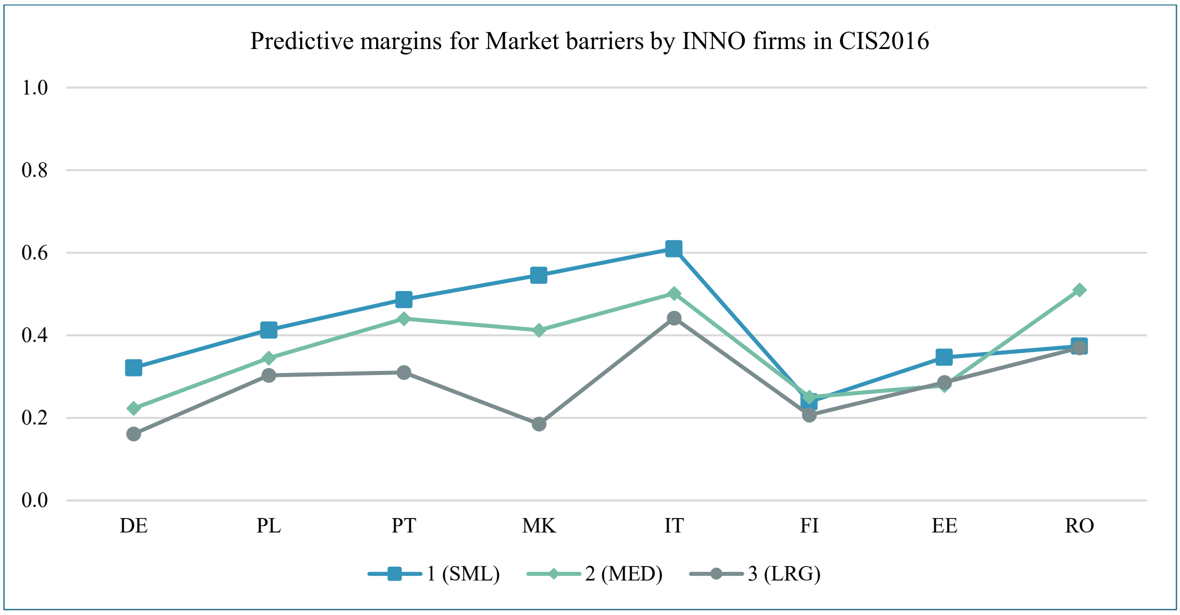

Figure B2. Predictive margins: Innovative firms assessing Market barriers as highly important across size classes in different countries.

Poland

First, descriptive statistics of firms that participated in the survey from each country are summarized (covering all four CIS releases, thus the 2012-2022 period).

PL	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	33,263	15%	32,791	17%	34,893	19%	36,207	30%
MED	8,974	36%	8,881	40%	9,678	38%	9,582	48%
LRG	2,029	63%	2,156	64%	2,374	62%	2,212	70%
Total Size class	**44,266**	**22%**	**43,828**	**24%**	**46,945**	**25%**	**48,001**	**35%**
Sector:								
PROD	32,739	23%	31,927	25%	32,814	26%	32,997	37%
SERV	11,527	19%	11,901	19%	14,131	23%	15,004	32%
Total Sector	**44,266**	**22%**	**43,828**	**24%**	**46,945**	**25%**	**48,001**	**35%**

Table B6. Descriptive statistics of the sample PL.

Poland 2014

Next, the predictive margins (and their statistical significance) across the selected countries and available releases were computed. (NON-INNO firms only for CIS 2014).

PL 2014	LFIN_IN	LFIN_EXT	L_SUBS	U_DMND	L_EMPL	L_PRTN
Non-innovative firms (NON-INNO)						
Size class:						
1 (SML)	0.378	0.267	0.250	0.150	0.173	0.156
	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]
2 (MED)	0.316	0.233	0.247	0.106	0.140	0.158
	[0.007***]	[0.007***]	[0.007***]	[0.006***]	[0.006***]	[0.006***]
3 (LRG)	0.245	0.187	0.196	0.101	0.097	0.085
	[0.019***]	[0.018***]	[0.018***]	[0.015***]	[0.014***]	[0.013***]
Sector:						
1 (PROD)	0.393	0.283	0.270	0.134	0.191	0.190
	[0.004***]	[0.004***]	[0.003***]	[0.003***]	[0.003***]	[0.003***]
2 (SERV)	0.291	0.200	0.193	0.161	0.104	0.049
	[0.006***]	[0.005***]	[0.005***]	[0.005***]	[0.004***]	[0.003***]
N	24,935	22,797	23,794	17,558	21,248	21,639

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B7. Predictive margins: PL 2014, size classes or sectors.

Poland 2016

PL 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.551	0.368	0.651	0.419	0.409	0.411	0.339	0.224
	[0.011***]	[0.011***]	[0.010***]	[0.010***]	[0.011***]	[0.011***]	[0.011***]	[0.009***]
2 (MED)	0.430	0.279	0.579	0.369	0.331	0.336	0.268	0.156
	[0.013***]	[0.011***]	[0.012***]	[0.011***]	[0.012***]	[0.013***]	[0.013***]	[0.010***]
3 (LRG)	0.327	0.189	0.554	0.315	0.308	0.287	0.205	0.121
	[0.020***]	[0.015***]	[0.021***]	[0.017***]	[0.020***]	[0.020***]	[0.019***]	[0.015***]
Sector:								
1 (PROD)	0.501	0.330	0.626	0.422	0.376	0.362	0.293	0.191
	[0.008***]	[0.008***]	[0.008***]	[0.008***]	[0.009***]	[0.009***]	[0.009***]	[0.007***]
2 (SERV)	0.390	0.217	0.571	0.266	0.338	0.390	0.306	0.176
	[0.016***]	[0.014***]	[0.015***]	[0.013***]	[0.015***]	[0.016***]	[0.016***]	[0.012***]
N	4,343	3,985	4,588	5,079	4,062	3,915	3,534	3,859

PL 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.799	0.733	0.847	0.709	0.627	0.691	0.587	0.487
	[0.007***]	[0.009***]	[0.006***]	[0.009***]	[0.010***]	[0.010***]	[0.011***]	[0.012***]
2 (MED)	0.764	0.704	0.834	0.623	0.622	0.645	0.561	0.487
	[0.017***]	[0.020***]	[0.015***]	[0.021***]	[0.022***]	[0.021***]	[0.024***]	[0.025***]
3 (LRG)	0.804	0.760	0.911	0.717	0.622	0.574	0.544	0.392
	[0.045***]	[0.052***]	[0.031***]	[0.056***]	[0.068***]	[0.074***]	[0.069***]	[0.072***]
Sector:								
1 (PROD)	0.830	0.770	0.878	0.725	0.672	0.715	0.629	0.532
	[0.007***]	[0.009***]	[0.006***]	[0.009***]	[0.010***]	[0.010***]	[0.011***]	[0.011***]
2 (SERV)	0.536	0.474	0.629	0.500	0.332	0.445	0.303	0.179
	[0.024***]	[0.025***]	[0.023***]	[0.024***]	[0.025***]	[0.027***]	[0.024***]	[0.022***]
N	3,401	2,787	3,625	3,158	2,603	2,524	2,458	2,184

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B8. Predictive margins: PL 2016, size classes or sectors.

Poland 2018

PL 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.345	0.247	0.483	0.360	0.279	0.368	0.469	0.168	0.122	0.090
	[0.008***]	[0.008***]	[0.009***]	[0.008***]	[0.008***]	[0.009***]	[0.009***]	[0.007***]	[0.006***]	[0.005***]
2 (MED)	0.269	0.172	0.389	0.257	0.260	0.270	0.374	0.132	0.087	0.079
	[0.010***]	[0.009***]	[0.012***]	[0.010***]	[0.011***]	[0.011***]	[0.012***]	[0.008***]	[0.007***]	[0.006***]
3 (LRG)	0.208	0.115	0.301	0.161	0.217	0.232	0.336	0.108	0.062	0.081
	[0.015***]	[0.012***]	[0.019***]	[0.013***]	[0.017***]	[0.018***]	[0.020***]	[0.013***]	[0.010***]	[0.011***]
Sector:										
1 (PROD)	0.348	0.237	0.485	0.350	0.291	0.353	0.457	0.164	0.123	0.082
	[0.007***]	[0.007***]	[0.008***]	[0.007***]	[0.008***]	[0.008***]	[0.008***]	[0.006***]	[0.006***]	[0.004***]
2 (SERV)	0.201	0.133	0.310	0.196	0.210	0.244	0.353	0.117	0.063	0.095
	[0.010***]	[0.008***]	[0.012***]	[0.009***]	[0.010***]	[0.011***]	[0.012***]	[0.008***]	[0.006***]	[0.007***]
N	5,743	5,754	5,486	5,953	5,251	4,854	5,442	4,988	5,177	5,952

PL 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.110	0.080	0.170	0.113	0.100	0.129	0.154	0.067	0.041	0.035
	[0.002***]	[0.002***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]	[0.003***]	[0.002***]	[0.001***]	[0.001***]
2 (MED)	0.102	0.074	0.161	0.100	0.090	0.113	0.136	0.064	0.042	0.046
	[0.005***]	[0.004***]	[0.006***]	[0.005***]	[0.005***]	[0.005***]	[0.005***]	[0.004***]	[0.003***]	[0.003***]
3 (LRG)	0.070	0.049	0.113	0.077	0.055	0.070	0.106	0.036	0.018	0.028
	[0.010***]	[0.009***]	[0.013***]	[0.011***]	[0.009***]	[0.010***]	[0.012***]	[0.008***]	[0.005***]	[0.007***]
Sector:										
1 (PROD)	0.111	0.079	0.184	0.115	0.107	0.122	0.159	0.068	0.044	0.037
	[0.002***]	[0.002***]	[0.003***]	[0.002***]	[0.002***]	[0.003***]	[0.003***]	[0.002***]	[0.002***]	[0.001***]
2 (SERV)	0.102	0.078	0.132	0.098	0.078	0.131	0.130	0.062	0.032	0.036
	[0.003***]	[0.003***]	[0.004***]	[0.003***]	[0.003***]	[0.004***]	[0.004***]	[0.003***]	[0.002***]	[0.002***]
N	24,904	24,372	24,544	24,556	23,943	23,017	23,792	23,551	23,760	25,082

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B9. Predictive margins: PL 2018, size classes or sectors.

Poland 2020

PL 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.239	0.178	0.343	0.270	0.209	0.204	0.296	0.126	0.107	0.068
	[0.005***]	[0.005***]	[0.006***]	[0.006***]	[0.005***]	[0.006***]	[0.006***]	[0.005***]	[0.004***]	[0.003***]
2 (MED)	0.201	0.147	0.300	0.217	0.196	0.186	0.265	0.087	0.088	0.072
	[0.008***]	[0.007***]	[0.010***]	[0.008***]	[0.008***]	[0.008***]	[0.009***]	[0.006***]	[0.006***]	[0.005***]
3 (LRG)	0.184	0.117	0.279	0.180	0.194	0.153	0.236	0.063	0.049	0.081
	[0.013***]	[0.010***]	[0.017***]	[0.013***]	[0.014***]	[0.014***]	[0.016***]	[0.009***]	[0.008***]	[0.009***]
Sector:										
1 (PROD)	0.277	0.207	0.363	0.292	0.231	0.210	0.305	0.114	0.109	0.066
	[0.006***]	[0.005***]	[0.006***]	[0.006***]	[0.006***]	[0.006***]	[0.006***]	[0.004***]	[0.004***]	[0.003***]
2 (SERV)	0.108	0.075	0.251	0.155	0.147	0.162	0.237	0.102	0.072	0.079
	[0.006***]	[0.005***]	[0.008***]	[0.007***]	[0.007***]	[0.007***]	[0.008***]	[0.006***]	[0.005***]	[0.005***]
N	9,590	9,557	8,980	9,526	8,514	7,953	8,571	8,302	8,505	9,597

PL 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.086	0.073	0.147	0.104	0.091	0.095	0.107	0.051	0.045	0.035
	[0.002***]	[0.002***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]	[0.002***]	[0.002***]	[0.002***]	[0.001***]
2 (MED)	0.074	0.060	0.112	0.077	0.056	0.055	0.087	0.042	0.033	0.033
	[0.004***]	[0.004***]	[0.005***]	[0.004***]	[0.004***]	[0.004***]	[0.005***]	[0.003***]	[0.003***]	[0.003***]
3 (LRG)	0.051	0.035	0.100	0.058	0.055	0.040	0.071	0.023	0.024	0.017
	[0.010***]	[0.008***]	[0.013***]	[0.010***]	[0.010***]	[0.009***]	[0.011***]	[0.007***]	[0.007***]	[0.006***]
Sector:										
1 (PROD)	0.106	0.082	0.175	0.118	0.105	0.093	0.136	0.069	0.054	0.037
	[0.003***]	[0.002***]	[0.003***]	[0.003***]	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.002***]	[0.002***]
2 (SERV)	0.041	0.047	0.072	0.064	0.048	0.079	0.039	0.012	0.023	0.030
	[0.002***]	[0.002***]	[0.003***]	[0.003***]	[0.002***]	[0.003***]	[0.002***]	[0.001***]	[0.002***]	[0.002***]
N	23,068	22,936	22,966	22,956	22,452	21,787	22,062	22,278	22,235	23,428

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B10. Predictive margins: PL 2020, size classes or sectors.

Portugal

PT	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	10,956	50%	11,333	62%	12,230	32%	12,913	45%
MED	2,710	65%	2,818	75%	3,016	56%	2,603	64%
LRG	401	85%	451	85%	511	75%	601	85%
Total Size class	**14,067**	**54%**	**14,602**	**65%**	**15,757**	**38%**	**16,117**	**49%**
Sector:								
PROD	11,213	53%	11,582	64%	12,366	38%	12,539	47%
SERV	2,854	56%	3,020	68%	3,391	40%	3,578	57%
Total Sector	**14,067**	**54%**	**14,602**	**65%**	**15,757**	**38%**	**16,117**	**49%**

Table B11. Descriptive statistics of the sample PT.

Portugal 2014

(NON-INNO firms only for CIS 2014.)

PT 2014	LFIN_IN	LFIN_EXT	L_SUBS	U_DMND	L_EMPL	L_PRTN
	Non-innovative firms (NON-INNO)					
Size class:						
1 (SML)	0.129	0.099	0.106	0.234	0.034	0.045
	[0.005***]	[0.004***]	[0.004***]	[0.008***]	[0.003***]	[0.003***]
2 (MED)	0.006	0.016	0.057	0.069	0.022	0.026
	[0.003**]	[0.004***]	[0.008***]	[0.012***]	[0.005***]	[0.005***]
3 (LRG)	0.000[1]	0.000	0.000	0.087	0.094	0.000
	[0***]	[0***]	[0***]	[0.049*]	[0.04**]	[0***]
Sector:						
1 (PROD)	0.126	0.097	0.110	0.205	0.039	0.047
	[0.005***]	[0.004***]	[0.005***]	[0.008***]	[0.003***]	[0.003***]
2 (SERV)	0.054	0.049	0.053	0.228	0.010	0.024
	[0.007***]	[0.006***]	[0.007***]	[0.014***]	[0.003***]	[0.005***]
N	5,988	5,870	5,964	3,625	5,712	5,752

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B12. Predictive margins: PT 2014, size classes or sectors.

[1] Predictive margins equal to zero means all respondent firms reported NONE importance of the obstacle.

Portugal 2016

PT 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.552	0.412	0.696	0.501	0.347	0.612	0.433	0.264
	[0.009***]	[0.009***]	[0.008***]	[0.008***]	[0.009***]	[0.009***]	[0.010***]	[0.008***]
2 (MED)	0.439	0.261	0.610	0.427	0.395	0.498	0.345	0.168
	[0.016***]	[0.014***]	[0.016***]	[0.016***]	[0.017***]	[0.018***]	[0.017***]	[0.014***]
3 (LRG)	0.279	0.111	0.457	0.294	0.339	0.297	0.227	0.088
	[0.036***]	[0.023***]	[0.046***]	[0.035***]	[0.040***]	[0.037***]	[0.036***]	[0.025***]
Sector:								
1 (PROD)	0.549	0.399	0.712	0.516	0.389	0.597	0.438	0.284
	[0.009***]	[0.008***]	[0.008***]	[0.008***]	[0.009***]	[0.009***]	[0.010***]	[0.008***]
2 (SERV)	0.427	0.263	0.537	0.376	0.254	0.515	0.303	0.060
	[0.015***]	[0.013***]	[0.016***]	[0.014***]	[0.015***]	[0.016***]	[0.016***]	[0.009***]
N	4,435	4,273	4,446	4,792	3,797	4,094	3,419	3,617

PT 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.838	0.803	0.863	0.751	0.661	0.732	0.621	0.539
	[0.017***]	[0.019***]	[0.015***]	[0.019***]	[0.023***]	[0.021***]	[0.028***]	[0.027***]
2 (MED)	0.333	No	0.323	0.170	0.119	0.136	0.453	0.342
	[0.122***]	observations	[0.123***]	[0.078**]	[0.051**]	[0.058**]	[0.078***]	[0.066***]
3 (LRG)	No	No	No	No	No	No	No	No
	observations	observations	observations	observations	observations	observations	observations	observations
Sector:								
1 (PROD)	0.822	0.803	0.828	0.696	0.585	0.648	0.611	0.546
	[0.017***]	[0.019***]	[0.017***]	[0.021***]	[0.024***]	[0.023***]	[0.028***]	[0.026***]
2 (SERV)	No	No	0.952	0.939	0.891	0.931	0.496	0.207
	observations	observations	[0.020***]	[0.026***]	[0.038***]	[0.025***]	[0.089***]	[0.066***]
N	484	426	555	500	439	456	338	386

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B13. Predictive margins: PT 2016, size classes or sectors.

Portugal 2018

PT 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.326	0.199	0.600	0.299	0.303	0.566	0.375	0.189	0.165	0.354
	[0.010***]	[0.009***]	[0.011***]	[0.009***]	[0.011***]	[0.011***]	[0.012***]	[0.009***]	[0.009***]	[0.012***]
2 (MED)	0.164	0.102	0.488	0.156	0.222	0.394	0.261	0.105	0.106	0.366
	[0.012***]	[0.010***]	[0.018***]	[0.012***]	[0.015***]	[0.017***]	[0.017***]	[0.011***]	[0.011***]	[0.019***]
3 (LRG)	0.192	0.056	0.378	0.190	0.160	0.293	0.179	0.095	0.045	0.335
	[0.027***]	[0.015***]	[0.042***]	[0.026***]	[0.029***]	[0.036***]	[0.030***]	[0.022***]	[0.015***]	[0.038***]
Sector:										
1 (PROD)	0.274	0.160	0.568	0.245	0.283	0.517	0.336	0.167	0.146	0.343
	[0.009***]	[0.007***]	[0.010***]	[0.008***]	[0.010***]	[0.010***]	[0.011***]	[0.008***]	[0.008***]	[0.011***]
2 (SERV)	0.268	0.166	0.537	0.279	0.240	0.468	0.319	0.136	0.124	0.400
	[0.015***]	[0.013***]	[0.019***]	[0.015***]	[0.017***]	[0.019***]	[0.018***]	[0.013***]	[0.012***]	[0.020***]
N	3,294	3,398	2,952	3,548	2,644	2,947	2,578	2,735	2,716	2,473

PT 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.210	0.155	0.371	0.182	0.169	0.368	0.222	0.140	0.130	0.235
	[0.006***]	[0.005***]	[0.007***]	[0.005***]	[0.006***]	[0.007***]	[0.006***]	[0.005***]	[0.005***]	[0.006***]
2 (MED)	0.244	0.184	0.389	0.189	0.212	0.356	0.255	0.150	0.110	0.288
	[0.015***]	[0.014***]	[0.017***]	[0.013***]	[0.015***]	[0.018***]	[0.016***]	[0.013***]	[0.012***]	[0.017***]
3 (LRG)	0.134	0.039	0.213	0.157	0.113	0.139	0.118	0.053	0.015	0.191
	[0.037***]	[0.021*]	[0.046***]	[0.038***]	[0.034***]	[0.038***]	[0.037***]	[0.025**]	[0.014]	[0.046***]
Sector:										
1 (PROD)	0.230	0.171	0.385	0.192	0.193	0.377	0.253	0.157	0.142	0.245
	[0.006***]	[0.006***]	[0.007***]	[0.006***]	[0.006***]	[0.007***]	[0.007***]	[0.006***]	[0.005***]	[0.007***]
2 (SERV)	0.159	0.112	0.327	0.151	0.112	0.317	0.132	0.083	0.075	0.229
	[0.01***]	[0.009***]	[0.013***]	[0.01***]	[0.009***]	[0.013***]	[0.01***]	[0.008***]	[0.007***]	[0.012***]
N	5,828	5,707	5,564	5,990	5,294	5,440	5,237	5,229	5,298	5,037

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B14. Predictive margins: PT 2018, size classes or sectors.

Portugal 2020

PT 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
	Innovative firms (INNO)									
Size class:										
1 (SML)	0.383	0.273	0.588	0.359	0.299	0.482	0.440	0.272	0.236	0.359
	[0.009***]	[0.008***]	[0.009***]	[0.008***]	[0.009***]	[0.009***]	[0.010***]	[0.009***]	[0.008***]	[0.010***]
2 (MED)	0.208	0.146	0.500	0.208	0.251	0.292	0.232	0.138	0.126	0.382
	[0.013***]	[0.011***]	[0.018***]	[0.013***]	[0.016***]	[0.016***]	[0.015***]	[0.012***]	[0.012***]	[0.018***]
3 (LRG)	0.135	0.066	0.353	0.154	0.161	0.197	0.112	0.086	0.055	0.275
	[0.024***]	[0.017***]	[0.040***]	[0.025***]	[0.029***]	[0.031***]	[0.025***]	[0.020***]	[0.017***]	[0.036***]
Sector:										
1 (PROD)	0.370	0.269	0.589	0.353	0.314	0.468	0.438	0.281	0.241	0.376
	[0.009***]	[0.008***]	[0.009***]	[0.008***]	[0.009***]	[0.009***]	[0.010***]	[0.009***]	[0.009***]	[0.010***]
2 (SERV)	0.236	0.146	0.490	0.230	0.198	0.323	0.231	0.109	0.108	0.315
	[0.012***]	[0.010***]	[0.015***]	[0.012***]	[0.013***]	[0.015***]	[0.013***]	[0.010***]	[0.010***]	[0.016***]
N	4,285	4,217	4,247	4,506	3,655	3,696	3,486	3,476	3,508	3,451

PT 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
	Non-innovative firms (NON-INNO)									
Size class:										
1 (SML)	0.266	0.204	0.405	0.262	0.188	0.347	0.272	0.198	0.183	0.238
	[0.007***]	[0.006***]	[0.007***]	[0.007***]	[0.006***]	[0.007***]	[0.007***]	[0.006***]	[0.006***]	[0.007***]
2 (MED)	0.196	0.137	0.285	0.144	0.142	0.262	0.215	0.147	0.101	0.223
	[0.016***]	[0.014***]	[0.019***]	[0.014***]	[0.014***]	[0.018***]	[0.017***]	[0.014***]	[0.013***]	[0.018***]
3 (LRG)	0.154	0.080	0.241	0.185	0.124	0.025	0.035	0.000	0.025	0.219
	[0.056***]	[0.043*]	[0.067***]	[0.059***]	[0.049**]	[0.025]	[0.031]	[0***]	[0.025]	[0.067***]
Sector:										
1 (PROD)	0.278	0.214	0.413	0.273	0.199	0.348	0.292	0.218	0.196	0.249
	[0.007***]	[0.007***]	[0.008***]	[0.007***]	[0.007***]	[0.008***]	[0.007***]	[0.007***]	[0.007***]	[0.007***]
2 (SERV)	0.161	0.113	0.295	0.139	0.112	0.277	0.141	0.079	0.074	0.181
	[0.012***]	[0.010***]	[0.015***]	[0.011***]	[0.010***]	[0.014***]	[0.012***]	[0.009***]	[0.009***]	[0.013***]
N	5,074	4,839	5,097	5,101	4,586	4,758	4,694	4,629	4,562	4,731

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B15. Predictive margins: PT 2020, size classes or sectors.

Estonia

EE	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	2,111	21%	2,205	43%	2,280	67%	2,245	62%
MED	610	40%	617	71%	632	85%	637	74%
LRG	105	59%	104	87%	95	97%	91	92%
Total Size class	**2,826**	**27%**	**2,926**	**51%**	**3,007**	**72%**	**2,973**	**65%**
Sector:								
PROD	1,827	27%	1,878	55%	1,903	75%	1,927	66%
SERV	999	25%	1,048	44%	1,104	66%	1,046	64%
Total Sector	**2,826**	**27%**	**2,926**	**51%**	**3,007**	**72%**	**2,973**	**65%**

Table B16. Descriptive statistics of the sample EE.

Estonia 2014

(NON-INNO firms only for CIS 2014.)

EE 2014	LFIN_IN	LFIN_EXT	L_SUBS	U_DMND	L_EMPL	L_PRTN
	Non-innovative firms (NON-INNO)					
Size class:						
1 (SML)	0.077	0.040	0.045	0.198	0.031	0.017
	[0.007***]	[0.005***]	[0.005***]	[0.014***]	[0.005***]	[0.003***]
2 (MED)	0.063	0.022	0.042	0.212	0.035	0.020
	[0.013***]	[0.008***]	[0.011***]	[0.031***]	[0.009***]	[0.007***]
3 (LRG)	0.046	0.046	0.023	0.148	0.045	0.000
	[0.032]	[0.032]	[0.023]	[0.069**]	[0.031]	[0***]
Sector:						
1 (PROD)	0.086	0.053	0.056	0.193	0.050	0.025
	[0.008***]	[0.007***]	[0.007***]	[0.015***]	[0.006***]	[0.005***]
2 (SERV)	0.053	0.011	0.025	0.212	0.001	0.004
	[0.009***]	[0.004***]	[0.006***]	[0.022***]	[0.001]	[0.003*]
N	1,909	1,887	1,928	1,003	1,870	1,852

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B17. Predictive margins: EE 2014, size classes or sectors.

Estonia 2016

EE 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.479	0.264	0.537	0.362	0.234	0.445	0.563	0.092
	[0.026***]	[0.022***]	[0.025***]	[0.022***]	[0.025***]	[0.028***]	[0.028***]	[0.018***]
2 (MED)	0.370	0.135	0.446	0.224	0.231	0.380	0.446	0.112
	[0.035***]	[0.024***]	[0.035***]	[0.028***]	[0.033***]	[0.039***]	[0.039***]	[0.027***]
3 (LRG)	0.358	0.130	0.409	0.210	0.362	0.285	0.420	0.068
	[0.076***]	[0.049***]	[0.09***]	[0.058***]	[0.08***]	[0.085***]	[0.113***]	[0.046]
Sector:								
1 (PROD)	0.481	0.263	0.547	0.391	0.246	0.414	0.515	0.083
	[0.024***]	[0.022***]	[0.024***]	[0.023***]	[0.024***]	[0.026***]	[0.027***]	[0.016***]
2 (SERV)	0.331	0.128	0.393	0.150	0.234	0.421	0.531	0.127
	[0.035***]	[0.022***]	[0.036***]	[0.023***]	[0.032***]	[0.041***]	[0.04***]	[0.029***]
N	602	633	606	693	496	512	502	435

EE 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.785	0.619	0.742	0.681	0.465	0.692	0.618	0.418
	[0.032***]	[0.041***]	[0.033***]	[0.04***]	[0.045***]	[0.039***]	[0.046***]	[0.043***]
2 (MED)	0.629	0.408	0.709	0.351	0.604	0.677	0.676	0.454
	[0.123***]	[0.128***]	[0.11***]	[0.116***]	[0.128***]	[0.107***]	[0.121***]	[0.143***]
3 (LRG)	No	No	0.482	0.496	No	0.627	No	No
	observations	observations	[0.354]	[0.355]	observations	[0.283**]	observations	Observations
Sector:								
1 (PROD)	0.768	0.587	0.751	0.647	0.362	0.726	0.601	0.355
	[0.038***]	[0.049***]	[0.039***]	[0.045***]	[0.054***]	[0.044***]	[0.052***]	[0.051***]
2 (SERV)	0.780	0.619	0.709	0.635	0.690	0.627	0.678	0.530
	[0.054***]	[0.065***]	[0.055***]	[0.068***]	[0.070***]	[0.062***]	[0.074***]	[0.069***]
N	184	157	197	157	123	164	128	140

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B18. Predictive margins: EE 2016, size classes or sectors.

Estonia 2018

EE 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.426	0.213	0.632	0.307	0.188	0.544	0.707	0.067	0.106	0.117
	[0.017***]	[0.014***]	[0.016***]	[0.015***]	[0.014***]	[0.018***]	[0.016***]	[0.010***]	[0.011***]	[0.011***]
2 (MED)	0.240	0.100	0.489	0.194	0.136	0.443	0.679	0.112	0.065	0.083
	[0.024***]	[0.016***]	[0.030***]	[0.020***]	[0.020***]	[0.029***]	[0.028***]	[0.019***]	[0.015***]	[0.015***]
3 (LRG)	0.238	0.069	0.572	0.157	0.120	0.382	0.732	0.035	0.060	0.118
	[0.062***]	[0.033**]	[0.072***]	[0.052***]	[0.050**]	[0.083***]	[0.071***]	[0.034]	[0.041]	[0.042***]
Sector:										
1 (PROD)	0.435	0.202	0.613	0.301	0.153	0.507	0.648	0.071	0.086	0.104
	[0.018***]	[0.014***]	[0.017***]	[0.016***]	[0.014***]	[0.018***]	[0.019***]	[0.010***]	[0.011***]	[0.011***]
2 (SERV)	0.268	0.126	0.567	0.226	0.200	0.524	0.782	0.094	0.108	0.117
	[0.020***]	[0.015***]	[0.024***]	[0.017***]	[0.020***]	[0.026***]	[0.020***]	[0.016***]	[0.015***]	[0.015***]
N	1,208	1,282	1,222	1,375	1,056	1,093	1,065	952	1,115	1,264

EE 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.335	0.172	0.454	0.199	0.093	0.375	0.442	0.135	0.063	0.116
	[0.022***]	[0.018***]	[0.023***]	[0.018***]	[0.014***]	[0.022***]	[0.025***]	[0.016***]	[0.011***]	[0.014***]
2 (MED)	0.101	0.084	0.207	0.089	0.068	0.119	0.275	0.000	0.000	0.156
	[0.039***]	[0.036**]	[0.054***]	[0.038**]	[0.033**]	[0.043***]	[0.066***]	[0***]	[0***]	[0.046***]
3 (LRG)	0.000	0.000	No obser-	No obser-	0.000	No obser-	No obser-	0.000	0.000	1.000
	[0***]	[0***]	vations	vations	[0***]	vations	vations	[0***]	[0***]	[0***]
Sector:										
1 (PROD)	0.295	0.171	0.340	0.173	0.095	0.209	0.445	0.111	0.054	0.041
	[0.027***]	[0.022***]	[0.028***]	[0.022***]	[0.017***]	[0.025***]	[0.033***]	[0.02***]	[0.014***]	[0.011***]
2 (SERV)	0.322	0.151	0.538	0.207	0.083	0.506	0.402	0.163	0.072	0.222
	[0.030***]	[0.024***]	[0.033***]	[0.026***]	[0.019***]	[0.032***]	[0.034***]	[0.026***]	[0.017***]	[0.027***]
N	517	517	524	548	489	497	438	453	495	552

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B19. Predictive margins: EE 2018, size classes or sectors.

Estonia 2020

EE 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	1.000[2]	0.131	0.474	0.207	0.087	0.240	0.506	0.101	0.061	No obser-
	[0***]	[0.012***]	[0.018***]	[0.014***]	[0.013***]	[0.020***]	[0.020***]	[0.012***]	[0.011***]	vations
2 (MED)	1.000	0.113	0.490	0.161	0.069	0.172	0.620	0.078	0.021	No obser-
	[0***]	[0.018***]	[0.031***]	[0.022***]	[0.025***]	[0.042***]	[0.033***]	[0.019***]	[0.014]	vations
3 (LRG)	1.000	0.000	0.554	0.123	0.000	0.247	0.658	0.117	0.000	No obser-
	[0***]	[0***]	[0.075***]	[0.043***]	[0***]	[0.213]	[0.08***]	[0.055**]	[0***]	vations
Sector:										
1 (PROD)	1.000	0.144	0.555	0.229	0.075	0.214	0.548	0.100	0.050	No obser-
	[0***]	[0.013***]	[0.020***]	[0.016***]	[0.014***]	[0.022***]	[0.021***]	[0.013***]	[0.012***]	vations
2 (SERV)	1.000	0.096	0.347	0.137	0.098	0.258	0.527	0.092	0.059	No obser-
	[0***]	[0.014***]	[0.025***]	[0.016***]	[0.020***]	[0.032***]	[0.028***]	[0.015***]	[0.015***]	vations
N	231	1,099	999	1,120	586	536	897	891	574	0

EE 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN[3]	D_PRIOR[3]
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	1.000	0.159	0.280	0.182	0.093	0.375	0.339	0.091	0.063	0.116
	[0***]	[0.016***]	[0.019***]	[0.016***]	[0.014***]	[0.022***]	[0.021***]	[0.013***]	[0.011***]	[0.014***]
2 (MED)	1.000	0.035	0.264	0.071	0.068	0.119	0.258	0.000	0.000	0.156
	[0***]	[0.017**]	[0.042***]	[0.024***]	[0.033**]	[0.043***]	[0.045***]	[0***]	[0***]	[0.046***]
3 (LRG)	1.000	0.000	0.330	0.000	0.000	0.000	0.331	0.000	0.000	0.000
	[0***]	[0***]	[0.272]	[0***]	[0***]	[0***]	[0.272]	[0***]	[0***]	[0***]
Sector:										
1 (PROD)	1.000	0.143	0.293	0.154	0.095	0.209	0.339	0.105	0.054	0.041
	[0***]	[0.018***]	[0.023***]	[0.018***]	[0.017***]	[0.025***]	[0.025***]	[0.018***]	[0.014***]	[0.011***]
2 (SERV)	1.000	0.129	0.252	0.175	0.083	0.506	0.304	0.067	0.072	0.222
	[0***]	[0.020***]	[0.028***]	[0.022***]	[0.019***]	[0.032***]	[0.031***]	[0.019***]	[0.017***]	[0.027***]
N	138	655	645	681	489	497	582	474	495	552

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B20. Predictive margins: EE 2020, size classes or sectors.

[2] Predictive margins equal to one means all respondent firms reported HIGH importance of the obstacle.
[3] For the obstacle non-innovative firms in Estonia reported the same results in CIS 2020 as in CIS 2018.

Romania

RO	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	15,479	11%	15,674	10%	15,937	15%	14,929	9%
MED	4,304	14%	4,411	11%	4,092	17%	3,631	13%
LRG	1,114	27%	1,072	18%	1,090	29%	1,114	28%
Total Size class	**20,897**	**13%**	**21,157**	**10%**	**21,119**	**16%**	**19,674**	**11%**
Sector:								
PROD	14,623	12%	14,244	10%	13,921	16%	12,524	11%
SERV	6,274	14%	6,913	11%	7,198	17%	7,150	10%
Total Sector	**20,897**	**13%**	**21,157**	**10%**	**21,119**	**16%**	**19,674**	**11%**

Table B21. Descriptive statistics of the sample RO.

Romania 2014

(NON-INNO firms only for CIS 2014.)

RO 2014	LFIN_IN	LFIN_EXT	L_SUBS	U_DMND	L_EMPL	L_PRTN
			Non-innovative firms (NON-INNO)			
Size class:						
1 (SML)	0.806	0.734	0.691	0.244	0.488	0.541
	[0.015***]	[0.019***]	[0.016***]	[0.006***]	[0.024***]	[0.020***]
2 (MED)	0.813	0.645	0.431	0.209	0.532	0.000
	[0.030***]	[0.046***]	[0.042***]	[0.012***]	[0.053***]	[0***]
3 (LRG)	0.744	0.560	0.560	0.156	0.281	0.000
	[0.067***]	[0.099***]	[0.081***]	[0.017***]	[0.106***]	[0***]
Sector:						
1 (PROD)	0.804	0.713	0.561	0.246	0.486	0.509
	[0.013***]	[0.018***]	[0.019***]	[0.007***]	[0.022***]	[0.022***]
2 (SERV)	1.000	1.000	0.867	0.204	0.625	0.706
	[0***]	[0***]	[0.021***]	[0.009***]	[0.148***]	[0.045***]
N	939	661	889	6,401	546	638

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B22. Predictive margins: RO 2014, size classes or sectors.

Romania 2016

RO 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.630	0.463	0.748	0.446	0.284	0.392	0.463	0.358
	[0.019***]	[0.023***]	[0.018***]	[0.019***]	[0.02***]	[0.023***]	[0.023***]	[0.021***]
2 (MED)	0.512	0.361	0.676	0.442	0.464	0.624	0.381	0.270
	[0.038***]	[0.037***]	[0.034***]	[0.032***]	[0.048***]	[0.041***]	[0.038***]	[0.029***]
3 (LRG)	0.345	0.214	0.424	0.315	0.352	0.442	0.490	0.263
	[0.061***]	[0.053***]	[0.063***]	[0.049***]	[0.065***]	[0.069***]	[0.066***]	[0.062***]
Sector:								
1 (PROD)	0.621	0.480	0.723	0.419	0.320	0.447	0.407	0.284
	[0.018***]	[0.021***]	[0.017***]	[0.017***]	[0.018***]	[0.019***]	[0.022***]	[0.018***]
2 (SERV)	0.375	0.049	0.648	0.496	0.000	0.000	0.557	0.469
	[0.044***]	[0.023**]	[0.035***]	[0.038***]	[0***]	[0***]	[0.038***]	[0.037***]
N	833	644	813	987	653	645	680	791

RO 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.825	0.717	0.838	0.573	0.601	0.656	0.663	0.579
	[0.012***]	[0.017***]	[0.011***]	[0.020***]	[0.018***]	[0.015***]	[0.019***]	[0.017***]
2 (MED)	0.843	0.736	0.870	0.592	0.471	0.632	0.576	0.570
	[0.020***]	[0.026***]	[0.017***]	[0.028***]	[0.033***]	[0.027***]	[0.035***]	[0.028***]
3 (LRG)	0.787	0.515	0.855	0.440	0.367	0.511	0.503	0.418
	[0.047***]	[0.060***]	[0.037***]	[0.068***]	[0.071***]	[0.069***]	[0.074***]	[0.06***]
Sector:								
1 (PROD)	0.827	0.704	0.840	0.641	0.569	0.639	0.663	0.562
	[0.012***]	[0.016***]	[0.011***]	[0.018***]	[0.017***]	[0.015***]	[0.019***]	[0.017***]
2 (SERV)	0.830	0.723	0.868	0.310	0.540	0.662	0.566	0.581
	[0.021***]	[0.025***]	[0.017***]	[0.035***]	[0.032***]	[0.025***]	[0.031***]	[0.027***]
N	1,321	1,087	1,539	888	1,062	1,346	883	1,193

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B23. Predictive margins: RO 2016, size classes or sectors.

Romania 2018

RO 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
	Innovative firms (INNO)									
Size class:										
1 (SML)	0.439	0.351	0.623	0.194	0.344	0.346	0.422	0.144	0.189	0.203
	[0.012***]	[0.011***]	[0.012***]	[0.010***]	[0.015***]	[0.012***]	[0.014***]	[0.010***]	[0.015***]	[0.011***]
2 (MED)	0.326	0.248	0.478	0.307	0.255	0.281	0.466	0.184	0.157	0.297
	[0.022***]	[0.021***]	[0.026***]	[0.023***]	[0.024***]	[0.025***]	[0.027***]	[0.020***]	[0.026***]	[0.023***]
3 (LRG)	0.169	0.107	0.322	0.203	0.132	0.192	0.360	0.120	0.072	0.236
	[0.027***]	[0.022***]	[0.036***]	[0.028***]	[0.028***]	[0.030***]	[0.037***]	[0.024***]	[0.026***]	[0.032***]
Sector:										
1 (PROD)	0.565	0.485	0.705	0.291	0.382	0.444	0.515	0.245	0.170	0.297
	[0.014***]	[0.014***]	[0.013***]	[0.013***]	[0.018***]	[0.015***]	[0.015***]	[0.014***]	[0.012***]	[0.014***]
2 (SERV)	0.133	0.041	0.303	0.093	0.209	0.141	0.120	0.010	0.000	0.084
	[0.012***]	[0.007***]	[0.018***]	[0.010***]	[0.016***]	[0.013***]	[0.017***]	[0.004***]	[0***]	[0.012***]
N	1,966	1,879	1,797	2,031	1,409	1,908	1,537	1,679	929	1,692

RO 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
	Non-innovative firms (NON-INNO)									
Size class:										
1 (SML)	0.265	0.266	0.447	0.218	0.228	0.320	0.339	0.189	0.121	0.204
	[0.005***]	[0.005***]	[0.006***]	[0.005***]	[0.005***]	[0.006***]	[0.006***]	[0.005***]	[0.004***]	[0.005***]
2 (MED)	0.257	0.194	0.318	0.202	0.177	0.215	0.254	0.141	0.055	0.255
	[0.010***]	[0.010***]	[0.011***]	[0.010***]	[0.009***]	[0.011***]	[0.011***]	[0.008***]	[0.006***]	[0.010***]
3 (LRG)	0.144	0.141	0.295	0.143	0.155	0.182	0.163	0.156	0.086	0.220
	[0.017***]	[0.018***]	[0.023***]	[0.017***]	[0.018***]	[0.021***]	[0.019***]	[0.017***]	[0.014***]	[0.020***]
Sector:										
1 (PROD)	0.368	0.289	0.512	0.305	0.287	0.369	0.396	0.264	0.167	0.292
	[0.006***]	[0.006***]	[0.006***]	[0.006***]	[0.006***]	[0.007***]	[0.007***]	[0.006***]	[0.006***]	[0.006***]
2 (SERV)	0.048	0.187	0.248	0.041	0.102	0.180	0.175	0.021	0.009	0.065
	[0.004***]	[0.007***]	[0.008***]	[0.004***]	[0.005***]	[0.007***]	[0.007***]	[0.003***]	[0.002***]	[0.005***]
N	8,468	8,435	9,276	8,116	7,966	8,149	8,417	7,685	7,107	8,715

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B24. Predictive margins: RO 2018, size classes or sectors.

Romania 2020

RO 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.054	0.030	0.000	0.027	0.305	0.020	0.000	0.000	0.206	0.097
	[0.010***]	[0.008***]	[0***]	[0.007***]	[0.016***]	[0.006***]	[0***]	[0***]	[0.020***]	[0.018***]
2 (MED)	0.615	0.426	0.448	0.123	0.622	0.557	0.404	0.197	0.000	0.722
	[0.043***]	[0.046***]	[0.033***]	[0.023***]	[0.059***]	[0.058***]	[0.036***]	[0.032***]	[0***]	[0.075***]
3 (LRG)	0.000	0.000	0.070	0.219	0.000	0.192	0.000	0.000	0.128	0.529
	[0***]	[0***]	[0.028**]	[0.037***]	[0***]	[0.030***]	[0***]	[0***]	[0.034***]	[0.121***]
Sector:										
1 (PROD)	0.203	0.161	0.372	0.077	0.500	0.125	0.449	0.197	0.192	0.000
	[0.021***]	[0.019***]	[0.030***]	[0.011***]	[0.024***]	[0.015***]	[0.042***]	[0.032***]	[0.017***]	[0***]
2 (SERV)	0.151	0.053	0.278	0.090	0.105	0.055	0.267	0.000	0.000	0.192
	[0.015***]	[0.010***]	[0.045***]	[0.016***]	[0.016***]	[0.011***]	[0.066***]	[0***]	[0***]	[0.019***]
N	620	630	310	830	746	592	183	152	506	312

RO 2020	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.171	0.097	0.150	0.117	0.152	0.039	0.099	0.078	0.126	0.046
	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.004***]	[0.003***]	[0.004***]	[0.003***]	[0.004***]	[0.002***]
2 (MED)	0.241	0.423	0.381	0.034	0.170	0.472	0.329	0.261	0.105	0.111
	[0.010***]	[0.017***]	[0.012***]	[0.007***]	[0.027***]	[0.020***]	[0.014***]	[0.013***]	[0.008***]	[0.009***]
3 (LRG)	0.098	0.073	0.079	0.204	0.103	0.000	0.029	0.000	0.000	0.090
	[0.014***]	[0.019***]	[0.016***]	[0.022***]	[0.029***]	[0***]	[0.012**]	[0***]	[0***]	[0.016***]
Sector:										
1 (PROD)	0.250	0.091	0.109	0.049	0.218	0.087	0.065	0.059	0.118	0.031
	[0.006***]	[0.005***]	[0.005***]	[0.003***]	[0.006***]	[0.004***]	[0.004***]	[0.003***]	[0.005***]	[0.002***]
2 (SERV)	0.064	0.173	0.288	0.185	0.054	0.081	0.225	0.173	0.127	0.100
	[0.004***]	[0.006***]	[0.007***]	[0.006***]	[0.004***]	[0.004***]	[0.007***]	[0.007***]	[0.006***]	[0.006***]
N	8,980	7,575	8,132	8,165	7,065	6,183	7,575	7,479	8,520	8,241

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B25. Predictive margins: RO 2020, size classes or sectors.

Finland

FI	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO	Surveyed firms	Percent of INNO
Size class:								
SML	4,602	52%	4,797	59%	4,525	55%	2,604	68%
MED	1,177	67%	1,315	77%	1,366	75%	907	24%
LRG	303	79%	300	84%	308	89%	231	94%
Total Size class	**6,082**	**56%**	**6,412**	**64%**	**6,199**	**61%**	**3,742**	**73%**
Sector:								
PROD	3,444	61%	3,731	70%	3,360	67%	3,382	75%
SERV	2,638	50%	2,681	56%	2,839	54%	360	61%
Total Sector	**6,082**	**56%**	**6,412**	**64%**	**6,199**	**61%**	**3,742**	**73%**

Table B26. Descriptive statistics of the sample FI.

Finland 2014

(No obstacles to innovation reported for CIS 2014.)

Finland 2016

(INNO firms only for CIS 2016.)

FI 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
	Innovative firms (INNO)							
Size class:								
1 (SML)	0.330	0.143	0.352	0.202	0.219	0.295	0.396	0.063
	[0.013***]	[0.009***]	[0.014***]	[0.011***]	[0.012***]	[0.014***]	[0.016***]	[0.008***]
2 (MED)	0.310	0.108	0.365	0.155	0.282	0.315	0.412	0.064
	[0.020***]	[0.013***]	[0.024***]	[0.016***]	[0.022***]	[0.024***]	[0.029***]	[0.014***]
3 (LRG)	0.292	0.035	0.213	0.169	0.202	0.250	0.287	0.066
	[0.042***]	[0.014**]	[0.050***]	[0.032***]	[0.044***]	[0.052***]	[0.059***]	[0.029**]
Sector:								
1 (PROD)	0.374	0.140	0.401	0.230	0.270	0.333	0.392	0.080
	[0.014***]	[0.010***]	[0.016***]	[0.012***]	[0.014***]	[0.015***]	[0.019***]	[0.009***]
2 (SERV)	0.251	0.106	0.272	0.132	0.183	0.243	0.398	0.038
	[0.015***]	[0.010***]	[0.018***]	[0.011***]	[0.015***]	[0.018***]	[0.021***]	[0.008***]
N	1,984	2,215	1,561	2,086	1,641	1,523	1,252	1,369

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B27. Predictive margins: FI 2016, size classes or sectors.

Finland 2018

FI 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Innovative firms (INNO)					
Size class:										
1 (SML)	0.187	0.079	0.174	0.080	0.151	0.160	0.239	0.059	0.041	0.172
	[0.010***]	[0.007***]	[0.011***]	[0.007***]	[0.010***]	[0.010***]	[0.013***]	[0.007***]	[0.005***]	[0.011***]
2 (MED)	0.130	0.065	0.120	0.099	0.161	0.145	0.242	0.027	0.053	0.176
	[0.014***]	[0.010***]	[0.015***]	[0.012***]	[0.017***]	[0.016***]	[0.022***]	[0.007***]	[0.01***]	[0.018***]
3 (LRG)	0.088	0.014	0.074	0.070	0.202	0.118	0.195	0.019	0.017	0.363
	[0.024***]	[0.008*]	[0.027***]	[0.020***]	[0.040***]	[0.032***]	[0.044***]	[0.014]	[0.012]	[0.050***]
Sector:										
1 (PROD)	0.177	0.071	0.160	0.080	0.187	0.176	0.234	0.038	0.033	0.166
	[0.011***]	[0.007***]	[0.012***]	[0.008***]	[0.012***]	[0.012***]	[0.015***]	[0.006***]	[0.006***]	[0.012***]
2 (SERV)	0.151	0.068	0.150	0.089	0.120	0.124	0.243	0.061	0.053	0.204
	[0.012***]	[0.008***]	[0.012***]	[0.009***]	[0.011***]	[0.012***]	[0.016***]	[0.008***]	[0.007***]	[0.014***]
N	2,169	2,572	1,815	2,390	1,791	1,797	1,523	1,891	1,992	1,768

FI 2018	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN	L_EXTKN	D_PRIOR
					Non-innovative firms (NON-INNO)					
Size class:										
1 (SML)	0.063	0.041	0.057	0.038	0.043	0.057	0.043	0.017	0.021	0.051
	[0.006***]	[0.005***]	[0.006***]	[0.005***]	[0.005***]	[0.006***]	[0.005***]	[0.003***]	[0.003***]	[0.005***]
2 (MED)	0.013	0.016	0.043	0.013	0.010	0.022	0.035	0.000	0.000	0.017
	[0.007**]	[0.007**]	[0.012***]	[0.006**]	[0.006*]	[0.008***]	[0.011***]	[0***]	[0***]	[0.008**]
3 (LRG)	0.000	0.000	0.031	0.000	0.035	0.000	0.000	0.000	0.000	0.089
	[0***]	[0***]	[0.031]	[0***]	[0.034]	[0***]	[0***]	[0***]	[0***]	[0.056]
Sector:										
1 (PROD)	0.063	0.042	0.053	0.029	0.044	0.031	0.046	0.018	0.018	0.071
	[0.008***]	[0.006***]	[0.007***]	[0.005***]	[0.007***]	[0.006***]	[0.007***]	[0.005***]	[0.005***]	[0.008***]
2 (SERV)	0.050	0.033	0.055	0.038	0.033	0.069	0.038	0.017	0.023	0.026
	[0.007***]	[0.005***]	[0.007***]	[0.006***]	[0.005***]	[0.008***]	[0.006***]	[0.004***]	[0.005***]	[0.005***]
N	2,039	2,071	2,064	2,105	2,060	1,979	1,902	1,658	1,702	2,009

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B28. Predictive margins: FI 2018, size classes or sectors.

Finland 2020

(No obstacles to innovation reported for CIS 2020.)

North Macedonia

MK	CIS 2014		CIS 2016		CIS 2018		CIS 2020	
	Surveyed firms	**Percent of INNO**	**Surveyed firms**	**Percent of INNO**	**Surveyed firms**	**Percent of INNO**	**Surveyed firms**	**Percent of INNO**
Size class:								
SML	1,735	32%	1,813	36%				
MED	482	40%	480	39%				
LRG	110	64%	107	53%				
Total Size class	**2,327**	**35%**	**2,400**	**37%**				
Sector:								
PROD	1,633	35%	1,619	36%				
SERV	694	36%	781	41%				
Total Sector	**2,327**	**35%**	**2,400**	**37%**				

Table B29. Descriptive statistics of the sample MK.

North Macedonia 2014

(No obstacles to innovation reported for CIS 2014.)

North Macedonia 2016

MK 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Innovative firms (INNO)				
Size class:								
1 (SML)	0.739	0.472	0.786	0.589	0.473	0.575	0.814	0.489
	[0.026***]	[0.031***]	[0.022***]	[0.027***]	[0.031***]	[0.032***]	[0.022***]	[0.032***]
2 (MED)	0.709	0.344	0.724	0.415	0.325	0.499	0.736	0.308
	[0.051***]	[0.053***]	[0.049***]	[0.044***]	[0.050***]	[0.055***]	[0.053***]	[0.052***]
3 (LRG)	0.356	0.104	0.495	0.067	0.231	0.258	0.401	0.099
	[0.088***]	[0.055*]	[0.083***]	[0.037*]	[0.077***]	[0.084***]	[0.090***]	[0.053*]
Sector:								
1 (PROD)	0.784	0.500	0.818	0.614	0.481	0.540	0.817	0.476
	[0.025***]	[0.034***]	[0.022***]	[0.027***]	[0.033***]	[0.034***]	[0.022***]	[0.033***]
2 (SERV)	0.542	0.286	0.620	0.328	0.318	0.519	0.651	0.300
	[0.044***]	[0.037***]	[0.040***]	[0.033***]	[0.039***]	[0.043***]	[0.044***]	[0.040***]
N	371	347	431	462	359	344	407	337

MK 2016	LFIN_IN	LFIN_EXT	H_COST	L_SUBS	U_DMND	H_COMP	L_EMPL	L_PRTN
				Non-innovative firms (NON-INNO)				
Size class:								
1 (SML)	0.898	0.675	0.894	0.733	0.562	0.607	0.861	0.631
	[0.016***]	[0.031***]	[0.017***]	[0.025***]	[0.029***]	[0.030***]	[0.020***]	[0.028***]
2 (MED)	0.887	0.740	0.936	0.774	0.515	0.736	0.906	0.777
	[0.036***]	[0.063***]	[0.026***]	[0.047***]	[0.066***]	[0.052***]	[0.038***]	[0.059***]
3 (LRG)	0.898	0.645	No	0.321	0.515	0.632	0.740	0.689
	[0.099***]	[0.208***]	observations	[0.268]	[0.204**]	[0.213***]	[0.148***]	[0.148***]
Sector:								
1 (PROD)	0.887	0.643	0.891	0.750	0.539	0.602	0.893	0.665
	[0.017***]	[0.035***]	[0.018***]	[0.025***]	[0.031***]	[0.033***]	[0.018***]	[0.029***]
2 (SERV)	0.924	0.781	0.943	0.700	0.592	0.699	0.761	0.618
	[0.026***]	[0.045***]	[0.023***]	[0.047***]	[0.050***]	[0.043***]	[0.050***]	[0.051***]
N	442	277	415	401	354	334	365	360

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table B30. Predictive margins: MK 2016, Size classes or sectors.

North Macedonia 2018

(No obstacles to innovation reported for CIS 2018.)

North Macedonia 2020

(No obstacles to innovation reported for CIS 2020.)

Appendix C

Exploring additional determinants of innovation

Gender diversity in the context of operational environment

Data were collected via an anonymized online questionnaire distributed to the R&D departments of 10 prominent manufacturing, construction, and oil & gas firms in Kazakhstan. Six of them qualified as *large* enterprises (having more than 500 employees) and four as *medium* (having between 200 and 500 employees). The firms were selected because they are on the *avant-garde* of innovation in Kazakhstan and because their apparent internationalization is conducive to a progressive attitude on gender issues.

- *Alstom*, a subsidiary of Alstom France, is the only manufacturer of electric locomotives and point machines in the Central Asian and Caucasian region and a major contributor to the revitalization of the rail industry in Kazakhstan.
- *Kazchrome* is a fully integrated mining and metals business covering all stages of the value chain. It is the world's largest high-carbon ferrochrome producer on a chrome content basis.
- *KLPE* is the main producer of large-capacity polyethylene in Kazakhstan, using gas from oil & gas fields as raw materials.
- *BI Group* is a large construction holding and a leader in the real estate market of Kazakhstan, consisting of divisions and directorates in various spheres of construction, development, and engineering.
- *SemArco*, is a subsidiary of the Archirodon Group, one of the top marine contractors internationally. SemArco undertakes in Kazakhstan the construction of ports and harbors, jetties, terminals, offshore structures, offshore pipelines, intakes, and outfalls, dredging and reclamation and generally all types of marine infrastructure.
- *Velesstroy* is a leading Russian construction company implementing in Kazakhstan oil & gas and electric power sector projects, as well as industrial & civil works.
- *KazMunayGaz (KMG)* is an operator for the exploration, production, refining and transportation of hydrocarbons, representing the state interests in the oil & gas sector of Kazakhstan.
- *North Caspian Operating Company (NCOC)* is an operating company for the North Caspian Sea Production Sharing Agreement (NCSPSA) which includes seven international oil companies.

- *Schlumberger* is a technology company that partners with customers to access energy. It operates in Kazakhstan as an oilfield services company.
- *TengizChevrOil (TCO)* is a joint venture led by Chevron to develop the Tengiz and Korolevskoye oil fields located in the north-eastern reaches of the Caspian Sea in Kazakhstan.

Overall, 421 anonymized online questionnaires were distributed to the personnel of these companies that were identified by the companies themselves as being involved in the innovation process (creative part and business process part).

Company	Sector	Size Class	Distributed surveys	Received surveys	Response rate
Alstom	Manufacturing	Large	51	32	63%
Kazchrome	Manufacturing	Large	23	13	57%
KLPE	Manufacturing	Medium	26	6	23%
Bi Group	Construction	Large	150	38	25%
Semarco	Construction	Medium	28	10	36%
Velesstroy	Construction	Medium	25	12	48%
KMG	Oil & gas	Medium	21	16	76%
NCOC	Oil & gas	Large	50	10	20%
Schlumberger	Oil & gas	Large	17	16	94%
TCO	Oil & gas	Large	30	16	53%
		Total:	**421**	**169**	**40%**

Table C1. Descriptive statistics of the surveyed sample, gender diversity, Kazakhstan.

The predictive margins (and their statistical significance) summarized in Table C2 reflect the predicted level of gender diversity in the implementation of innovative products and services in the company and the launching the business activities that enhance innovation productivity in the company, as well as, the level of digital skills and digital know-how across the gender.

Variable	Total	Males	Females
Gender:			
1 (Male)	0.188	0.184	
	[0.038] ***	[0.036] ***	
2 (Female)	0.143		0.148
	[0.044] ***		[0.045] ***
Size class:			
1 (Medium)	0.277	0.389	0.161
	[0.073] ***	[0.113] ***	[0.085] *
2 (Large)	0.138	0.132	0.141
	[0.031] ***	[0.037] ***	[0.054] ***
Sector:			
1 (Manufacturing)	0.192	0.236	0.135
	[0.052] ***	[0.065] ***	[0.089]
2 (Construction)	0.122	0.110	0.110
	[0.047] ***	[0.054] *	[0.074]
3 (Oil & gas)	0.195	0.199	0.179
	[0.052] ***	[0.070] ***	[0.072] ***
N	169	108	61

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table C2. Predictive margins: Implementation of innovation.

Variable	Total	Males	Females
Gender:			
1 (Male)	0.201	0.203	
	[0.039] ***	[0.038] ***	
2 (Female)	0.234		0.230
	[0.055] ***		[0.054] ***
Size class:			
1 (Medium)	0.269	0.356	0.208
	[0.071] ***	[0.111] ***	[0.093] **
2 (Large)	0.194	0.165	0.239
	[0.036] ***	[0.040] ***	[0.066] ***
Sector:			
1 (Manufacturing)	0.253	0.284	0.198
	[0.058] ***	[0.069] ***	[0.103] *
2 (Construction)	0.176	0.124	0.224
	[0.056] ***	[0.061] **	[0.099] **
3 (Oil & gas)	0.203	0.171	0.250
	[0.053] ***	[0.067] **	[0.082] ***
N	169	108	61

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table C3. Predictive margins: Launching the business activities.

Variable	Total	Males	Females
Gender:			
1 (Male)	0.224	0.212	
	[0.040] ***	[0.039] ***	
2 (Female)	0.118		0.131
	[0.040] ***		[0.054] ***
Size class:			
1 (Medium)	0.259	0.302	0.171
	[0.070] ***	[0.100] ***	[0.087] **
2 (Large)	0.157	0.184	0.114
	[0.033] ***	[0.044] ***	[0.048] **
Sector:			
1 (Manufacturing)	0.146	0.165	0.138
	[0.045] ***	[0.057] ***	[0.091]
2 (Construction)	0.146	0.204	0.051
	[0.052] ***	[0.079] **	[0.052]
3 (Oil & gas)	0.258	0.301	0.180
	[0.058] ***	[0.083] ***	[0.072] **
N	169	108	61

** significant at 10%; ** significant at 5%; *** significant at 1%*

Table C4. Predictive margins: Digital skills and digital know-how.

Diversity processes in innovation hotspots

The descriptive statistics on the data and variables used are summarized in Table C5.

Statistics	PCTF	WI (%)	POP
Minimum	1,089	9.2	70,644
Maximum	34,324	20.7	15,539,937
Mean	5,067	14.7	3,004,007
Standard deviation	6,803	3.0	3,419,395
Shapiro-wilk w	0.607	0.972	0.752
Shapiro-wilk p	<0.001	0.570	<0.001

Table C5. Descriptive statistics of the variables, gender diversity, clusters.

Policy interventions aiming innovation hotspots

First, the data on the world's top-100 innovation clusters based on their patent activity from a working paper released by WIPO [37] was summarized in Table C6.

For each top cluster, the key technology field was noted based on the WIPO technology concordance table linking International Patent Classification (IPC) symbols with the sectors including:

- Electrical Engineering (EE);
- Instruments (IN);
- Chemistry (CH);
- Mechanical Engineering (ME); and
- Other Fields (OF).

#	Cluster localization	Country	Total filings	Top entity filings	Top sector	Top sector filings	Total PRO filings
1	Tokyo–Yokohama	JP	94,079	6,021	EE	5,927	2,728
2	Shenzhen–Hong Kong	CN	41,218	13,355	EE	16,982	495
3	San Jose–San Francisco, CA	US	34,324	2,231	EE	6,281	1,167
4	Seoul	KR	34,187	5,675	EE	3,555	3,692
5	Osaka–Kobe–Kyoto	JP	23,512	2,445	EE	1,951	988
6	San Diego, CA	US	16,908	9,485	EE	3,990	524
7	Beijing	CN	15,185	2,141	EE	3,432	2,885
8	Boston–Cambridge, MA	US	13,819	843	CH	1,714	2,294
9	Nagoya	JP	13,515	5,730	ME	1,757	257
10	Paris	FR	13,461	1,036	ME	1,090	1,292
11	New York, NY	US	12,215	513	CH	1,331	1,515
12	Frankfurt–Mannheim	DE	11,813	2,327	CH	851	508
13	Houston, TX	US	9,825	1,267	OF	2,466	511
14	Stuttgart	DE	9,528	4,545	ME	1,077	219
15	Seattle, WA	US	8,396	3,518	EE	2,905	353
16	Cologne–Dusseldorf	DE	7,957	613	CH	565	191
17	Chicago, IL	US	7,789	904	EE	576	428
18	Eindhoven	NL	7,222	6,131	IN	1,293	65
19	Shanghai	CN	6,639	285	EE	631	757
20	Munich	DE	6,578	770	ME	526	289
21	London	GB	6,548	399	EE	471	498
22	Tel Aviv	IL	5,659	232	EE	724	504
23	Daejeon	KR	5,507	1,090	EE	589	1,867
24	Stockholm	SE	5,211	2,298	EE	1,397	26
25	Los Angeles, CA	US	5,027	422	IN	478	1,066
26	Minneapolis, MN	US	4,422	624	IN	1,446	177
27	Portland, OR	US	4,146	2,036	EE	829	104
28	Nuremberg–Erlangen	DE	4,049	1,680	EE	466	336
29	Irvine, CA	US	3,965	317	IN	860	119
30	Berlin	DE	3,632	461	EE	309	458

#	Cluster localization	Country	Total filings	Top entity filings	Top sector	Top sector filings	Total PRO filings
31	Zurich	CH	3,615	228	IN	231	289
32	Philadelphia, PA	US	3,172	279	CH	504	606
33	Plano, TX	US	3,147	538	OF	481	145
34	Helsinki–Espoo	FI	3,045	639	EE	597	82
35	Singapore	SG	2,996	458	IN	147	1,064
36	Basel	CH	2,804	297	CH	367	84
37	Raleigh–Durham, NC	US	2,775	308	CH	258	547
38	Hitachi	JP	2,648	858	EE	527	13
39	Copenhagen	DK	2,613	272	CH	290	311
40	Hamamatsu	JP	2,496	626	ME	287	82
41	Washington, DC	US	2,491	289	CH	366	389
42	Cincinnati, OH	US	2,481	826	IN	638	102
43	Bengaluru	IN	2,479	228	EE	439	82
44	Sydney	AU	2,380	107	IN	209	257
45	Rotterdam–The Hague	NL	2,235	273	ME	125	501
46	Atlanta, GA	US	2,162	154	IN	238	203
47	Montreal, QC	CA	2,124	232	EE	253	204
48	Toronto, ON	CA	2,094	63	EE	155	209
49	Austin, TX	US	2,089	230	EE	409	263
50	Lyon	FR	2,063	196	CH	165	186
51	Wilmington, DL	US	2,046	964	CH	168	80
52	Barcelona	ES	2,003	174	CH	188	347
53	Regensburg	DE	2,001	734	EE	516	24
54	Brussels–Leuven	BE	1,994	94	CH	122	245
55	Cambridge	GB	1,984	133	EE	161	206
56	Grenoble	FR	1,969	872	EE	213	969
57	Moscow	RU	1,915	36	CH	117	36
58	Milan	IT	1,909	162	CH	101	82
59	Hamburg	DE	1,870	206	CH	264	58
60	Melbourne	AU	1,799	92	CH	104	293
61	Madrid	ES	1,796	239	EE	199	462
62	Malmö	SE	1,737	339	EE	219	14
63	Guangzhou	CN	1,670	114	EE	114	322
64	Indianapolis, IN	US	1,596	361	CH	137	109
65	Lausanne	CH	1,580	436	CH	119	196
66	Ottawa, ON	CA	1,560	259	EE	471	67
67	Hartford, CT	US	1,540	1012	ME	610	22
68	Busan	KR	1,470	82	IN	76	326
69	Gothenborg	SE	1,461	324	EE	137	4
70	Rochester, NY	US	1,414	540	ME	140	143
71	Vienna	AT	1,403	60	CH	109	146
72	Phoenix, AZ	US	1,378	212	EE	163	23
73	Vancouver, BC	CA	1,362	93	CH	75	159
74	Heidenheim–Aalen	DE	1,352	296	IN	215	3
75	Cleveland, OH	US	1,346	131	IN	149	268
76	Boulder, CO	US	1,319	77	IN	153	92
77	Yokkaichi	JP	1,318	515	EE	426	9
78	Haifa	IL	1,298	140	IN	241	113
79	Salt Lake City, UT	US	1,293	193	IN	250	207

#	Cluster localization	Country	Total filings	Top entity filings	Top sector	Top sector filings	Total PRO filings
80	Ann Arbor, MI	US	1,289	352	CH	92	380
81	Pittsburgh, PA	US	1,283	164	IN	115	273
82	Aachen	DE	1,279	170	EE	115	134
83	Shizuoka	JP	1,241	597	IN	139	4
84	Buhl	DE	1,223	594	ME	538	6
85	Hangzhou	CN	1,213	321	EE	205	146
86	Albany, NY	US	1,184	651	EE	117	77
87	St. Louis, MO	US	1,138	131	CH	118	155
88	Oxford	GB	1,134	313	CH	94	355
89	Baltimore, MD	US	1,089	493	CH	163	565
90	Daegu	KR	1,085	131	IN	84	283
91	Amsterdam	NL	1,063	309	CH	91	98
92	Kuala Lumpur	MY	1,049	525	EE	120	713
93	Clermont-Ferrand	FR	1,041	771	ME	274	31
94	Nanjing	CN	1,030	104	EE	90	318
95	Mumbai	IN	1,012	68	CH	156	60
96	Pune	IN	1,006	233	CH	158	246
97	Shikokuchuo	JP	995	896	IN	520	6
98	Toulouse	FR	991	100	ME	99	177
99	Hannover	DE	979	140	ME	150	70
100	Suzhou	CN	956	74	OF	76	57

Table C6. Cluster ranking based on total 2011-2015 PCT filings.